NASA CONTRACTOR REPORT 177324

(NASA-CR-177324) CONTROL AND MODELING OF A CELSS (CONTROLLED ECOLOGICAL LIFE SUPPORT SYSTEM) (California Univ.) 85 p HC A05/MF A01 CSCL 06K

N85-16472

Unclas G3/54 13251

Control and Modeling of a CELSS (Controlled Ecological Life Support System)

D. M. Auslander
R. C. Spear
P. S. Babcock
M. H. Nadel

NASA Cooperative Agreement NCC 2-67
October 1983

NASA

CELSS

NASA CONTRACTOR REPORT 177324

Control and Modeling of a CELSS (Controlled Ecological Life Support System)

D. M. Auslander
R. C. Spear
P. S. Babcock
M. H. Nadel
University of California
College of Engineering
Berkeley, CA 94720

Prepared for
Ames Research Center
Under Contract NCC 2-67

NASA
National Aeronautics and
Space Administration

Ames Research Center
Moffett Field, California 94035

CELSS

TABLE OF CONTENTS

Preface

This final report covers work performed under NASA grant NCC 2-67 during 1981, 1982, and the first half of 1983. This research on control and modeling of CELSS continues under NASA grant NCC 2-257.

The report is divided into three major areas: uncertain and poorly defined systems, resource allocation, and control of systems with delay and closure. The motivation for dividing the research into these three areas is covered in the Summary. The technical background, a summary of our findings thus far, and a listing of future work, or research tasks, is presented for each of these areas.

Summary

This project is concerned with research topics that arise from the conceptualization of control for closed life support systems, that is, life support systems in which all or most of the mass is recycled (these are abbreviated CELSS for controlled ecological life support system). The topics that we have emphasized are modeling and control of uncertain and poorly defined systems, resource allocation in closed life support systems, and control structures for systems with delay and closure.

This choice of topics is based on studies done to-date for the purpose of identifying unique dynamic control problems associated with closed life support systems. These are a combination of generic problems that, while very important to CELSS control, have not received wide attention from the control community, and specific problems that arise from the structure and performance constraints of the CELSS itself.

Of these topics, the first, modeling and control of uncertain and poorly defined systems, has received the most attention so far. It consists of several generic areas that will be critical to control of a CELSS, including parameter identification and sensitivity analysis for models of biological systems, design of feedback control systems for systems with uncertainty, and design of nonlinear controllers. Because of the complexity and inclusion of biological elements (including humans) in a CELSS, any global or detail level control must be able to deal effectively with poorly defined and nonlinear systems. The major mechanism used to approach both the complexity and the uncertainty in an efficient manner is the use of

performance criteria expressed as binary variables. This approach has proven to be particularly effective for biological systems as well as providing an effective basis for the design of engineered systems.

The work in resource allocation centers on two challenging problems. The first is unique to CELSS: the definition of survival as the performance criterion for system design and supervisory control. The second, high dimensionality and widely spaced time scales, while not a problem only in CELSS systems, must be always be handled in an ad hoc fashion by tailoring the solution methodology to the problem's specific structure. Resource allocation is classically formulated as a dynamic programming problem. We have developed a dynamic programming formulation with probability of survival as its performance criterion, and will use that to attack problems of time-scale, model uncertainty, and dimensionality.

A parallel and complementary approach that we are using to specify the nature of a CELSS supervisory control system is to examine abstractions of the CELSS structure to determine the nature of control problems that arise and the types of control structures that can deal effectively with them. The primary structural problems we have isolated so far have their basis in the presence of time delay, nonlinearities, and closure. These lead to extremely difficult to control dynamic behaviors, including chaotic behavior which is a seemingly random response that arises from purely deterministic sources.

Introduction

Control of a closed life support system involves a series of control levels, each with its own performance criteria and unique control problems. At the highest level, the overall goal of the control system is survival, which makes this control problem distinctly different from virtually all systems to which control theory has been applied. In conventional applications of control theory, the goal at the highest level is almost always associated with some kind of economic measure, often profitability. Another unique factor, which is common to several CELSS control levels, is that the system not only includes biological elements, but the humans who constitute part of the biological component also operate the control system.

We have approached the CELSS control problem from both a specific and a generic point of view. In the generic sense, we have attempted to identify problem areas that are important to CELSS systems but need further research work before they can be considered for use in a CELSS control system.

The generic studies we have been interested in have centered on questions of uncertainty and poorly-defined systems. Because of the complexity of a CELSS, and because of the heavy component of biological elements, we believe that no modeling effort, no matter how elaborate, will ever be able to predict the behavior of a CELSS sufficiently well for

a straightforward deterministic control to be applied. To this end, we are assuming that the system to be controlled will have to be described in a probabilistic form of some sort, so we have concentrated on a means of parameter fitting for models that can be applied in such situations and control system design methods that can be used with systems that are nonlinear as well as uncertain. Numerical/statistical methods are notoriously high in their computational requirements. To alleviate that problem as much as possible, we are working with methods in which performance criteria can be expressed in binary form. These methods have proved particularly successful with biological systems, because, it appears, these systems have extremely well defined behaviors even though substantial individual parameter variation must be tolerated.

We began looking at CELSS-specific control problems by constructing a simple computer model of a CELSS and performing a variety of simulation experiments with it. By using several randomly applied pertubations (such as a temporary malfunction in a system component) we noted that system behaviors could be generated in which the failure did not occur until long after the pertubation had been removed. This suggested that the long time delay of plant growth might be a dominant dynamic factor. Because of the closed nature of the system, and the presence of many nonlinearities, the possibility of producing very complex dynamic behaviors was suggested by these results. These behaviors, if actually present in a real CELSS, would mean that application of simple, "intuitive" control rules might not lead to satisfactory control. We are now abstracting this component of a CELSS behavior into a series of even simpler models to look at control methodologies that appear to have some hope of success in dealing with such systems.

Yet another view of CELSS control is as a resource allocation problem. This resource allocation problem differs from traditional optimization problems in two ways: first, the performance criterion is survival, for which we must find a suitable analytical formulation, and, secondly, there is no obvious "cost" associated with the use of any particular resource, as there is in a traditional industrial allocation problem. Our approach to this is, initially, through variants on the techniques of dynamic programming. Dynamic programming's major limitation is that the computational load goes up prohibitively as the complexity of the system increases. As with the statistically based modeling and control efforts described above, much of our work must go into means for reducing the computational load.

Uncertainty and Poorly Defined Systems

Much of the work that we have carried out has been concerned with questions of uncertainty in the modeling and control of poorly defined systems. The general approach has been largely based on the ideas first described in Spear and Hornberger (1980, 1981) and Hornberger and Spear (1980). These papers describe a sensitivity analysis procedure which focuses on a region of system parameter space rather than a single point. Since the regional sensitivity idea is central to much of our subsequent work it is important to describe the central concepts in some detail.

For clarity of exposition, we restrict our attention to a specific

class of models and introduce nomenclature which will be required subsequently. Assume the processes are to be modeled by a set of first order differential equations. (Different mathematical structures can be dealt with in an analogous way). Let these equations be given in the form:

$$(d/dt)x(t) = x'(t) = f[x(t),P,z(t)]$$

where x(t) is the state vector and z(t) is a set of time variable functions which include input or forcing functions. The vector P is a set of constant parameters described more fully below. Thus, for P, z(t) and x(0) specified, x(t) is the solution of the system of equations and is a deterministic or a stochastic function of time as determined by the nature of z(t). For simplicity of exposition, z(t) will be treated hereafter as a deterministic function of t.

Each element of the vector P is defined as a random variable the distribution of which is a measure of our uncertainty in the "real" but unknown value of the parameter. These parameter distributions are formed from data available from the literature and from experience with similar structures. For example, the literature suggests that the maximum growth rate of _Chlorella vulgaris_ is almost certainly between 1.5 and 2.5 per day at water temperatures near 25 degrees C. Interpreting these limits as the range of a rectangularly distributed random variable, and forming similar _a priori_ estimates for the other elements of P result in the definition of an ensemble of models. Some of these models will, we hope, mimic the real system with respect to the behavior of interest.

Turning now to the question of behavior, recall that every sample value of P, drawn from the _a priori_ distribution, results in a unique state

trajectory, $x(t)$. Following the usual practice, we assume that there are a set of observed variables $y(t)$, calculable from the state vector, which are important to the problem at hand. So, for each randomly chosen parameter set P^*, there corresponds a unique observation vector $y^*(t)$. Since the elements of $y(t)$ are observed (that is we assume they are measured in the real system), it is sensible to define behavior in terms of $y(t)$. For example, suppose y_i is the concentration of phytoplankton in a body of water and the problem in question concerns unwanted algal blooms due to nutrient enrichment. Then, there is some value of y_i above which a bloom is defined to have occurred and the behavior is defined by this critical value.

In general, a number of behavior categories can be used. Without loss of generality, however, we can consider the case for which behavior is defined in a binary sense, i.e., it either occurs or does not occur for a given scenario and set of parameters P. It follows that a rule must be specified for determining the occurrence or non-occurrence of the behavior on the basis of the pattern of $y(t)$. It is also possible that the behavior might depend on the vector $z(t)$. For example, suppose one element of $z(t)$ was water temperature. We might be interested only in extreme values of $y(t)$ when adjusted or controlled for temperature variations. In any event, the detailed definition of behavior is problem-dependent and, for present purposes, it is sufficient to keep in mind that a set of numerical values of P leads to a unique time function $y(t)$ which, in turn, determines the occurrence or non-occurrence of the behavior conditioned, perhaps, by $z(t)$.

We have now presented the class of models to be studied and described how we propose to deal with parametric uncertainty. For a given behavior and set of parameter distributions P, it is possible to explore the properties of the ensemble via computer simulation studies. In particular, a random choice of the parameter vector P from the predefined distributions leads to a state trajectory x(t), an observation vector y(t) and, via the behavior-defining algorithm, to a determination of the occurrence or non-occurrence of the behavior. A repetition of the process for many sets of randomly chosen parameters results in a set of sample parameter vectors for which the behavior was observed and a set for which the behavior was not observed. The key idea is then to attempt to identify the subset of physically, chemically or biologically meaningful parameters which appear to account for the occurrence or non-occurrence of the behavior.

Ranking the elements of P in order of importance in the behavioral context is accomplished through an analysis of the Monte-Carlo results. The essential concept can best be illustrated by considering a single element, Pk, of the vector P and its *a priori* cumulative distribution, as shown in Figure 1. Recall that the procedure is to draw a random sample from this parent distribution (a similar procedure is followed for all other elements of P), run the simulation with this value and record the observed behavior and the total vector P therewith associated. A repetition of this procedure results in two sets of values for Pk, one associated with the occurrence of the behavior B, and the other without the behavior, B'. That is, we have split the distribution F(Pk) into two parts as indicated in the figure. This particular example would suggest that Pk was important to the behavior since F(Pk) is clearly divided by the

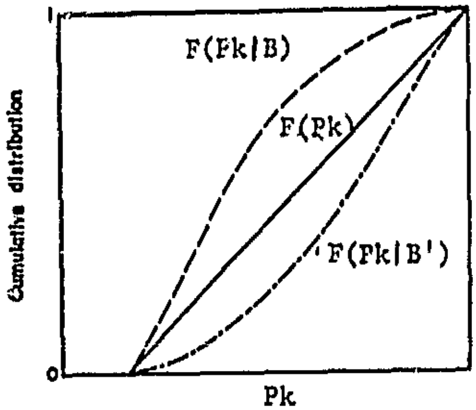


Figure 1: Cumulative distribution functions for parameter Pk. F(Pk) = parent, a priori distribution, F(Pk|B) = distribution of Pk in the behaviour category, F(Pk|B') = Distribution of Pk in the non-behaviour category.

behavioral classification. Alternatively, if the sample values under B and B' appeared both to be from the original distribution F(Pk), then we would conclude that Pk was not important.

For the case where z(t) is a deterministic function of time, the parameter space is cleanly divided by the behavioral mapping; that is, there is no ambiguity regarding whether a given parameter vector results in B or B'. The analysis then focuses on the determination of which parameters or combinations of parameters are most important in distinguishing between B and B'. We will restrict the discussion to the case for which the parameter vector mean is zero and the parameter covariance matrix is the identity matrix. (A suitable transformation can always be found to convert the general problem to this case). The problem of identifying how the behavioral mapping separates the parent parameter space can then be approached by examining induced mean shifts and induced covariance structure.

For example, we can base a sensitivity ranking on a direct measure of the separation of the cumulative distribution functions, F(Pk|B) and F(Pk|B'). In particular, we often utilize the statistic:

$$d(m,n) = \sup \mid Sn(x) - Sm(x) \mid$$

where Sn and Sm are sample distribution functions corresponding to F(Pk|B) and F(Pk|B') for n behaviors and m non-behaviors. The statistic d(m,n) is that used in the Kolmogorov-Smirnov two sample test and both its asymptotic and small sample distributions are known for any continuous cumulative distribution function F(Pk|B) and F(Pk|B'). Since Sn and Sm are estimates of F(Pk|B) and F(Pk|B'), we see that d(m,n) is the maximum

vertical distance between these two curves and the statistic is, therefore, sensitive not only to differences in central tendency but to any difference in the distribution functions. Thus, large values of d(m,n) indicate that the parameter is important for simulating the behavior and, at least in some cases where induced covariance is small, the converse is true for small values of that statistic.

In general, however, ranking on the basis of the separation in the distribution function along the original axes of the parameter space (the individual parameter values) is not sufficient. It is possible, for example, that the first and second moments for a simple parameter might exhibit no separation and yet this parameter could be crucial to a successful simulation by virtue of a strong correlation with other parameters under the behavior. For example, Figure 2 depicts a two-dimensional space for which the cumulative distribution would not separate under the behavioral classification. Nevertheless, both parameters are important in determining whether the behavior occurs. Clearly, it is the interaction between parameters which is crucial, and information on the covariance between the two parameters may give insight into the degree of sensitivity in a case such as this.

As discussed below, however, interaction between parameters seem seldom to be of the sort revealed by correlation techniques or principal components analyses. It appears that such interactions are often nonlinear and a major element of this proposal is to investigate means of more reliably detecting and understanding parametric interactions as determinants of system behavior.

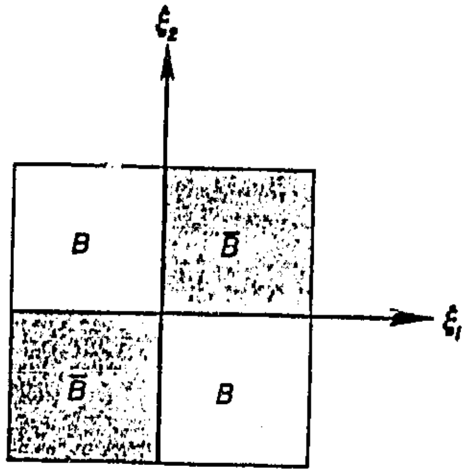


Figure 2: Schematic diagram of a two parameter case for which separation under the behavioural classification is total but for which discrimination by univariate tests is not possible.

Since the original development and application of the foregoing ideas in the context of the Peel Inlet, eutrophication studies in Western Australia (Spear and Hornberger, 1980) several investigators have applied these concepts in the analysis of diverse problems. Spear and Hornberger (1981) studied energy trade-off questions related to the Solar Power Satellite (SPS). Fedra applied the technique, more or less intact, to various water pollution problems in Austria (Fedra, 1980, 1982). Auslander (1982) successfully applied these ideas to the elucidation of spatial effects on the stability of a food-limited moth population, the model in this case being given by partial differential equations. Whitehead and Hornberger (1983) used the regional sensitivity approach as the first stage of a parameter estimation scheme, the second stage of which utilized the Extended Kalman Filter (EKF). In this study an initial attempt to use the EKF alone failed when the algorithm did not converge, A reduction of the parameter set using the sensitivity analysis led to convergence of the EKF when applied to the reduced parameter vector.

A second and closely related line of research has been focused on the application of these same concepts to the control of parametrically poorly defined systems. It is here that the major applications to CELSS problems are foreseen and much of this work has been supported by the CELSS program under NASA Cooperative agreement NCC-2-67. The initial work along this line was carried out by John Stahr in his analysis of a CELSS-like model (Stahr, Auslander, Spear, and Young, 1981). The importance of this work was its demonstration that CELSS may well be susceptible to long-term

dynamic failure modes and that the design of control systems to deal with such phenomena will be crucial to mission success.

In Stahr's work and in subsequent control studies the behavioral definition of the sensitivity analysis is replaced by a binary performance criterion, adequate or inadequate system performance. The process parameters are usually assumed poorly known and the issue is to find a fixed set of controller parameters that will yield a high probability of adequate performance in spite of the process uncertainty. The strength of the Monte-Carlo approach in this application is that the mapping from the parameter space to the performance outcome can tolerate nonlinearities in the controlled process and can be used to design nonlinear controllers as will be discussed below. Another major advantage is that the effect of process parameters on system performance is also revealed in the analysis which can be used to specify those sub-processes which should be made the object of estimation experiments or be investigated for the possibility of redesign to allow more favorable dynamic performance.

The first results of this aspect of the research were published in 1982 (Auslander, Spear, and Young, 1982). This paper applied the simulation-based approach to some simple systems that could also be analyzed to a greater or lesser degree by conventional methods. The object was to contrast the information developed during the analysis and the results obtained. The conclusions were favorable to the simulation approach since the results were direct and easily interpretable in practical terms and, of course, conventional methods cannot easily handle the process parameter uncertainty.

A second effort was carried out along similar lines by Spear and Hornberger (1983). The investigation concerned the effect of process parameter uncertainty on the control of dissolved oxygen in a river. This problem was interesting in the CELSS context since the process models had biological elements which were subject to some uncertainty and, also, it was a problem to which several sophisticated control schemes had been applied in the past. It was found that the most straightforward and practical of these previous system designs was significantly influenced by modest levels of parametric uncertainty (+/- 25%). Moreover, the simulation-based approach revealed a particularly simple control design which delivered a reasonably high probability of adequate performance under the process uncertainty.

A significant development of the rather straightforward extension of the sensitivity ideas to control mentioned above was carried out under NASA support by G.E. Young (1982). The thrust of Young's work was to apply the foregoing ideas to discrete time nonlinear controllers for both perfectly known and poorly known processes. In general, Young found the simulation-based approach to be quite practical and workable when applied to fairly simple process models (up to order four). He also found that nonlinear controllers gave better performance than linear designs although his process models generally included saturation phenomena which made them nonlinear from the outset. Young has provided some guidance for reducing the sample size required to arrive at acceptable designs in the case of process parameter uncertainty. However, more complex models will be

required to explore more thoroughly some of these strategies for sample size containment. Nevertheless, the methodology proposed by Young for nonlinear controller design would appear to merit further investigation.

It is a common feature of both the control and sensitivity versions of the simulation-based procedure that most of the useful information is gained from the univariate statistics. That is, it is unusual to detect correlations between parameters under the behavior that exceed 0.3 with or without coordinate rotation and the situations as depicted in Figure 2 above seem not to occur in practice. It is beginning to become clear that this is not because of a lack of interesting and informative interactions between parameters, but probably because these interactions are not susceptible to linear multivariate methods. This will be addressed below.

RESEARCH TASKS

1) In the context of both the sensitivity analysis and nonlinear control, we propose to apply new statistical methods to investigate the interaction between parameters inder the binary mappin associated with the behavioral criterion and the adequate performance criterion respectively.

Recall that, in the sensitivity context, the issue is to determine which elements of the parameter vector, $\underline{P}$, either singly or in interaction with other elements, are important in causing the occurrence of the behavior, B. As noted above, with regard to our past work, interactions between two or more parameters seldom seemed important on its own. We have concluded that this is not because less obvious interactions do not exist, but because

they are seldom revealed by standard statistical methods based on correlation-like analyses with or without coordinate transformations (Hornberger and Spear, 1981).

It transpires that this same issue is currently of some interest in statistical research. In particular, at Stanford, Friedman and Stuetzle have developed a novel approach to the analysis of multivariate point clouds based on computer graphics (Appendix I). The general concept is termed "projection pursuit" and has both regression and classification variants. The literature on these methods is sparse (Friedman and Stuetzle, 1981; Friedman and Stuetzle, 1982a) but includes various internal reports from the Stanford Linear Accelerator and the Department of Statistics. Nevertheless, it is clear that their approach is almost uniquely suited for our purposes and it is very much in the spirit of our approach to the problems of uncertainty in systems design. One of us has visited the Stanford group and determined that there are several computer codes for batch processing versions of their methods that can be implemented on our VAX. Of these, the most highly developed is a regression program, but a classification program will be available shortly.

The key to the approach is to find "interesting" projections of the point cloud onto 2 or 3 dimensional subspaces. In the batch mode, this involves definition of what is interesting in terms of a figure of merit and, subsequently, maximizing this figure by directed searching procedures (a simplified Rosenbrock method is apparently the usual method used by the Stanford group). Once structure is found, it is removed and

further structure is sought. At present, considerable art seems to be involved in choosing the smoothing algorithm applied to the projections (Friedman and Stuetzle, 1982b). However, we propose to apply these methods to CELSS control problems and we expect that they will result in a significant increase in our insight into the sensitivity problem and in our ability to design controllers. The specific tasks to be accomplished are:

a) Obtain projection pursuit software from Stanford and adapt it for our VAX.
b) Apply the pursuit algorithms to simple sensitivity problems selected for their analytical tractability.
c) Apply the pursuit algorithms to a complex hydro-chemical model under investigation by Hornberger.
d) Apply the pursuit algorithms to a CELSS model.

2) We propose to continue the attack developed by Young on nonlinear controller design and on the control of nonlinear systems containing parameter uncertainty. There are no general methods for the design of nonlinear controllers despite the fact that there is ample reason to suspect that better performance can be expected in many cases. Young has shown that variations of the sensitivity methodology have considerable promise in dealing with this design issue. His work dealt with rather sinple plant models and it is of interest to extend his approach to more realisitic models of CELSS components.

A second aspect of this task is to extend Young's work on the control of processes with parametric uncertainty. This problem was also

addressed by others in our group (Spear and Hornberger, 1983) and it seems likely that a marriage of the two approaches might pay dividends. Spear and Hornberger asked how great was the influence of process parametric uncertainty on the behavior of a particular controlled system containing biological components. The influence was found to be considerable and they proceeded to develop a robust controller design. This involved attempting to locate a point in the controller parameter subspace which would assure a reasonably high probability of adequate performance in spite of process parmeter uncertainty. we proppose to apply the projectio pursuit concept to this problem, perhaps via logistic regression, as a stage of analyses prior to Young's procedure which is a type of search algorithm directed at refining the "design." That is, Young is also seeking a set of control parameters that maximizes the probability of adequate performance, but he requires a starting point from which to conduct a directed search.

The specific tasks to be accomplished are:

a) Select several CELSS component models of limited complexity.

b) Apply Young's approach for known process parameters and determine the effect of increasing model complexity.

c) Select CELSS models of medium complexity.

d) Apply Spear-Hornberger approach to find initial design point.

e) Apply Young's second method to obtaining refined controller design.

Resource Allocation in CELSS

In order to design a controller for any system, we need precise mathematical descriptions of the system behavior, the available control inputs and the goals the control system must meet. For a CELSS, control can be exerted by manipulating various processing rates, such as, recycler and dehumidifier operation rates, and by deciding how much of each "resource" (water, food, etc.) to allocate to each "activity" in each time period. This suggests that CELSS control can be viewed as a resource allocation problem.

Since the resource allocations can only be made at fixed time intervals, application of analytically-based techniques requires a discrete-time model for the dynamics of a CELSS. For our preliminary analysis, the state of the system is assumed to consist of two types of variables -- supplies of the various resources and deficits that accumulate when demands for resources aren't met. More realistic models may have additional state variables, such as plant biomass.

Deficit dynamics are inherently discrete time and obey relationships of the form:

$$D(k+1) = D(k) - F(k)S(k) + B(k)$$

where (for a single resource):

$D(k)$ is the deficit at the kth time step

S(k) is the available supply

F(k) is the fractional allocation of supply to make up the deficit

and B(k) is a random baseline demand.

For models with several resources, the functional form of the deficit dynamics is unchanged, but D, S, and B become vectors while F becomes a matrix.

Supply dynamics can be related to chemical kinetics. If we consider a single chemical reaction:

$$A \longrightarrow B$$

we can define a reaction coordinate, z, such that z = 1 means that one mole of A has been converted to one mole of B. The reaction kinetics can be completely described in terms of z and follow the equation:

$$dz/dt = f(z,t)$$

where f is, in general, a nonlinear function. The supply of A at the (k+1)th time step is then:

$$A(k+1) = A(k) - [z(k+1) - z(k)]$$

where the bracketed term is obtained by integrating the kinetic equation. This integration will usually have to be performed numerically.

Note that the supply of B is uniquely determined by mass conservation:

$$A(k) + B(k) = \text{constant}$$

When there are several chemical reactions, the reaction coordinate, z, becomes a vector. We also need to account for changes in the supplies resulting directly from allocation decisions; this is illustrated in an example below.

To complete the problem specification, we need a performance criterion for the control system to meet. The goal of a CELSS is survival. Therefore, the appropriate performance index for a stochastic CELSS model is the probability of survival. Let Pi be the conditional probability of survival at the (i + 1)th time step given survival at the ith time step. Once the probability distributions of the baseline demands and any other uncertain parameters of the model are specified, these transition probabilities can be expressed as functions only of the state, control input and time. Thus we can write:

$$Pi = g(x(i),u(i),i) = g(i)$$

where the notation x is used for the state vector and u for the control vector in order to conform to conventional control systems notation.

Since failure to survive at one time step implies failure to survive at all future time steps, the overall probability of survival is the product of the transition probabilities. That is, the probability of survival at time N given survival at time k is given by:

$$Jk = g(k)g(k+1).....g(N-1)$$

Using this expression for the "cost-to-go" the resource allocation problem can be solved by means of dynamic programming. Application of the principle of optimality (Bellman, 1957) results in the recursion formula for the optimal cost and control:

$$J^*(x(k)) = \max \{g(k)J^*(x(k+1))\}$$

where the maximization is over all admissible values of u(k); that is, over all controls that satisfy mass conservation and constraints on operation rates of recyclers, dehumidifiers and other processing elements. The

optimal control, $u^*(x(k),k)$ is that control which produces the optimal cost, $J^*(x(k))$. This optimal control need not be unique; if it is not, additional criteria must be applied to select which control to use.

If the CELSS is assumed to survive at time N then $J^*(x(N))= 1$ for all $x(N)$ and the optimal control can be found for any state at time N-1. Thus the functional equation for the optimal cost and control can be solved backwards from a fixed final time by quantizing the state space and searching over all admissible controls for each state and time. The major limitation to the application of this method is the state-space quantization, which leads to a prohibitively high computational load for high-order systems.

The utility of this approach for CELSS control can be demonstrated by considering the simple system shown schematically in Figure 3. Water is allocated to humans and plants, supplies of water internal to plants and humans are converted to atmospheric water vapour with reaction coordinates z1 and z2 respectively and a dehumidifier converts atmospheric water vapour to liquid water with reaction coordinate z3. If the humans receive insufficient water, a deficit accumulates. The baseline demand for water by humans is assumed to be:

B(k)= [1 + G(SQRT(H/Wt))]Ba

where: B(k) is baseline demand at kth time step

H is atmospheric water vapour

Wt is total water

Ba is average baseline demand for water by humans

and G is a zero mean Gaussian random variable.

Since G is Gaussian, B(k) and, hence, the human water deficit, D(k), are

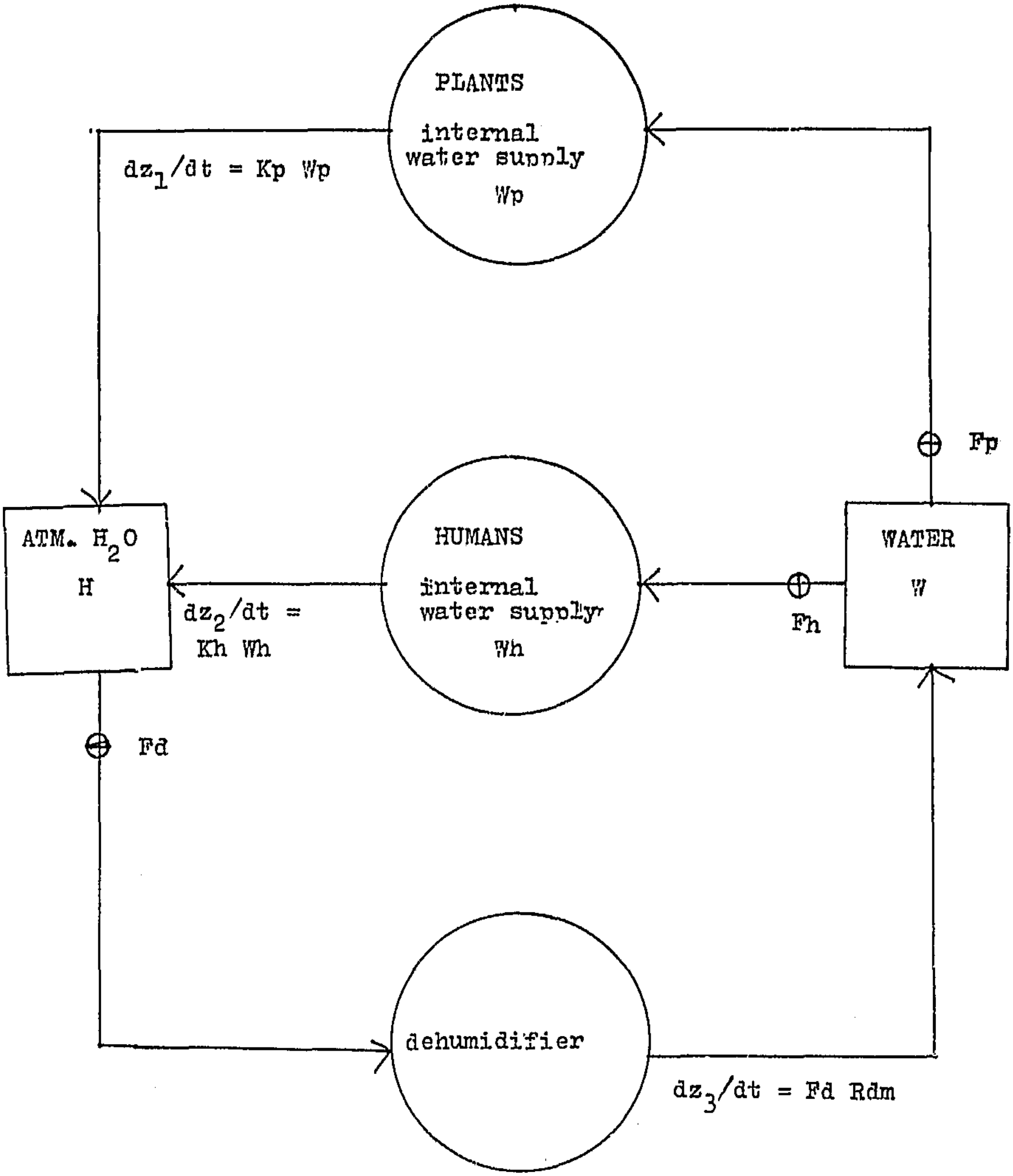


FIGURE 3 SIMPLE CELSS MODEL WITH ONE RESOURCE

also Gaussian; therefore, the deficit can be completely described by its mean and variance. If the mean and variance are used as state variables and the differential equations for the reaction coordinates are integrated, we obtain the state equations given in Figure 4a. The numerical values are shown in Figure 4b.

To complete the model, two survival criteria are imposed. The supply of water internal to the plants must remain above a specified minimum; that is:

$$Wp(k) > Wmin$$

Since the random parameter, G, affects only the deficit and not the supplies, this is a deterministic requirement. The second survival requirement is that the human water deficit be acceptably small, i.e.

$$D(k) < Dmax$$

The probability of this occurring is given by:

$$Prob\{D(k) < Dmax\} = PHI[(Dmax - M)/SQRT(V)]$$

where M is the mean deficit, V is the variance of the deficit and PHI is the Gaussian distibution function. A flow chart for determining the transition probabilities given the state and control vectors is given in Figure 5.

The three control inputs are the allocations of water to plants and humans respectively, expressed as fractions of the water storage, and the dehumidifier operation rate, expressed as a fraction of the maximum possible operation rate. One possible (non-optimal) control scheme is to allocate the average baseline demand for water to the humans and to use

$$Wp(k+1) = \exp(-Kp\ DT)(Wp(k) + Fp(k)W(k))$$

$$Wh(k+1) = \exp(-Kh\ DT)(Wh(k) + Fh(k)W(k))$$

$$H(k+1) = H(k) + (1 - \exp(-Kh\ DT))(Wh(k) + Fh(k)W(k)) + (1 - \exp(-Kp\ DT))(Wp(k) + Fp(k)W(k)) - Fd\ Rdm\ DT$$

$$M(k+1) = M(k) - Fh(k)W(k) + Ba$$

$$V(k+1) = V(k) + v^2\ Ba^2\ H(k)/Wt$$

with $W(k) = Wt - H(k) - Wp(k) - Wh(k)$

(a) STATE EQUATIONS FOR SIMPLE CELSS MODEL

Variable	Definition	Value
Wp	plant water supply	nonconstant
Wh	human water supply	nonconstant
H	atm. H_2O	nonconstant
M	mean deficit	nonconstant
V	variance of deficit	nonconstant
W	water supply	nonconstant
Wt	total water	7000 moles
DT	time step	3 hours
Kh	reaction rate	.8316/hour
Kp	reaction rate	.005/hour
Rdm	max. dehumidifier rate	67 moles/hour
Ba	baseline water demand	12.5 moles
v	variance of activity parameter (see text)	0.4
Dmax	max. deficit	40 moles
Wmin	minimum Wp	200 moles

(b) NUMERICAL VALUES
FIGURE 4

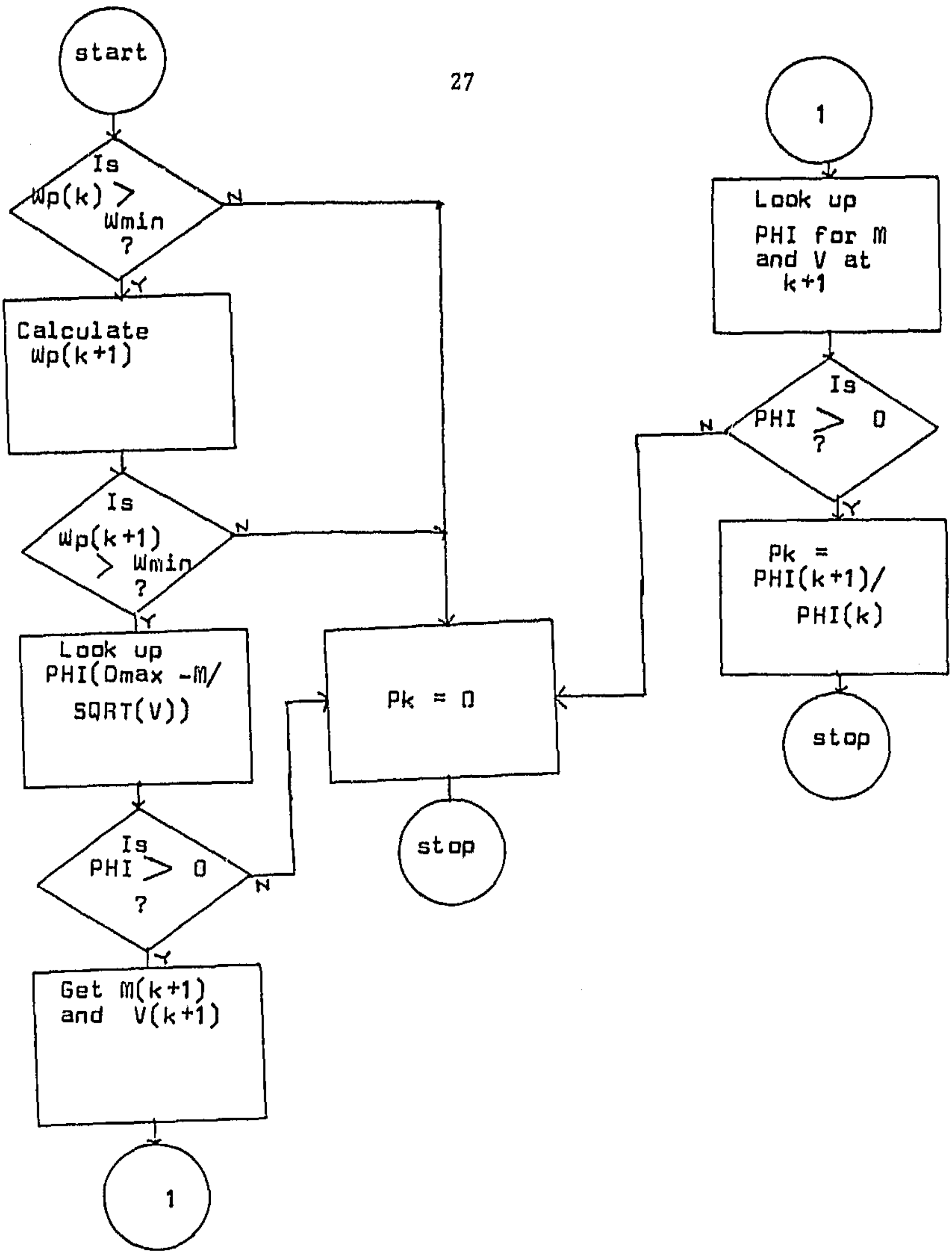


FIGURE 5 FLOW CHART FOR CALCULATING TRANSITION PROBABILITY

proportional control to determine the water allocation to plants and the dehumidifier operation rate. The specific control considered here is:

$$Fp = 0.01523\ Wp / W$$

$$Fh = Ba / W$$

$$Fd = 0.25 + 1.43E\text{-}4\ H$$

with saturation limits (0,1) for the fractional water allocation to plants, Fp, and the dehumidifier operation rate, Fd, and (0,1-Fp) for the fractional water allocation to humans, Fh. Note that the deficit does not affect the control inputs in this scheme.

The optimal control can be calculated explicitly for this example. The result is:

$$Fp = (203.1 - Wp) / W$$

$$Fh = (M + Ba) / W$$

$$Fd > (H + 0.9175\ Wh + 0.9175\ M + 14.52)/Rdm$$

where Rdm is the maximum possible dehumidifier operation rate. The saturation limits are the same as above. Note the nonuniqueness of the optimal dehumidifier operation rate. The optimal control computes Fd in such a way that the atmospheric humidity and, hence, the increase in the variance of the human water deficit will be minimized. Suppose some value of Fd less than 1 can reduce the atmospheric humidity to zero; call this value Fdcrit. Clearly any value of Fd between Fdcrit and 1 inclusive will also reduce the humidity to zero and will, therefore, also be optimal. This nonuniqueness is not really a problem, since all optimal values for Fd result in the same probability of survival. Indeed, in this case, they also result in a unique state at the next time step.

Each of the controllers was studied by simulating system performance for 250 time steps (31.25 days). In the absence of perturbetions, both controllers converge to steady states with guaranteed survival, i.e. probability of survival = 1. However, the nonoptimal control converges more slowly and the steady state obtained using it results in a higher variance of deficit and a larger supply of water internal to the plants. These results are shown in Figure 6 with solid lines for the optimal control and dashed lines for the nonoptimal.

The effects of a dehumidifier failure from time steps 24 to 32 were then considered. With the optimal control, survival is still guaranteed and a new steady state is reached one time step after the dehumidifier resumes operation. The nonoptimal control cannot ensure survival in this case. Thirty time steps after the disturbance is removed (i.e. after the dehumidifier is restored) a new steady state is reached but the probability of survival associated with that steady state is only 0.9. Figure 7 shows that the decreased survival probability comes about because of the higher variance of deficit associated with the nonoptimal control.

A more serious problem is the effect of an error in the baseline demand for water by humans. The actual average baseline demand is 12.5; implementation of the nonoptimal control with an assumed baseline demand of 12.3 results in a survival probability that decreases continually and reaches 0.3 by the end of 250 time steps, as shown in Figure 8. Because the deficit is not fed back, the controller is unaware of the gradual increase in mean deficit which is ultimately responsible for the failure.

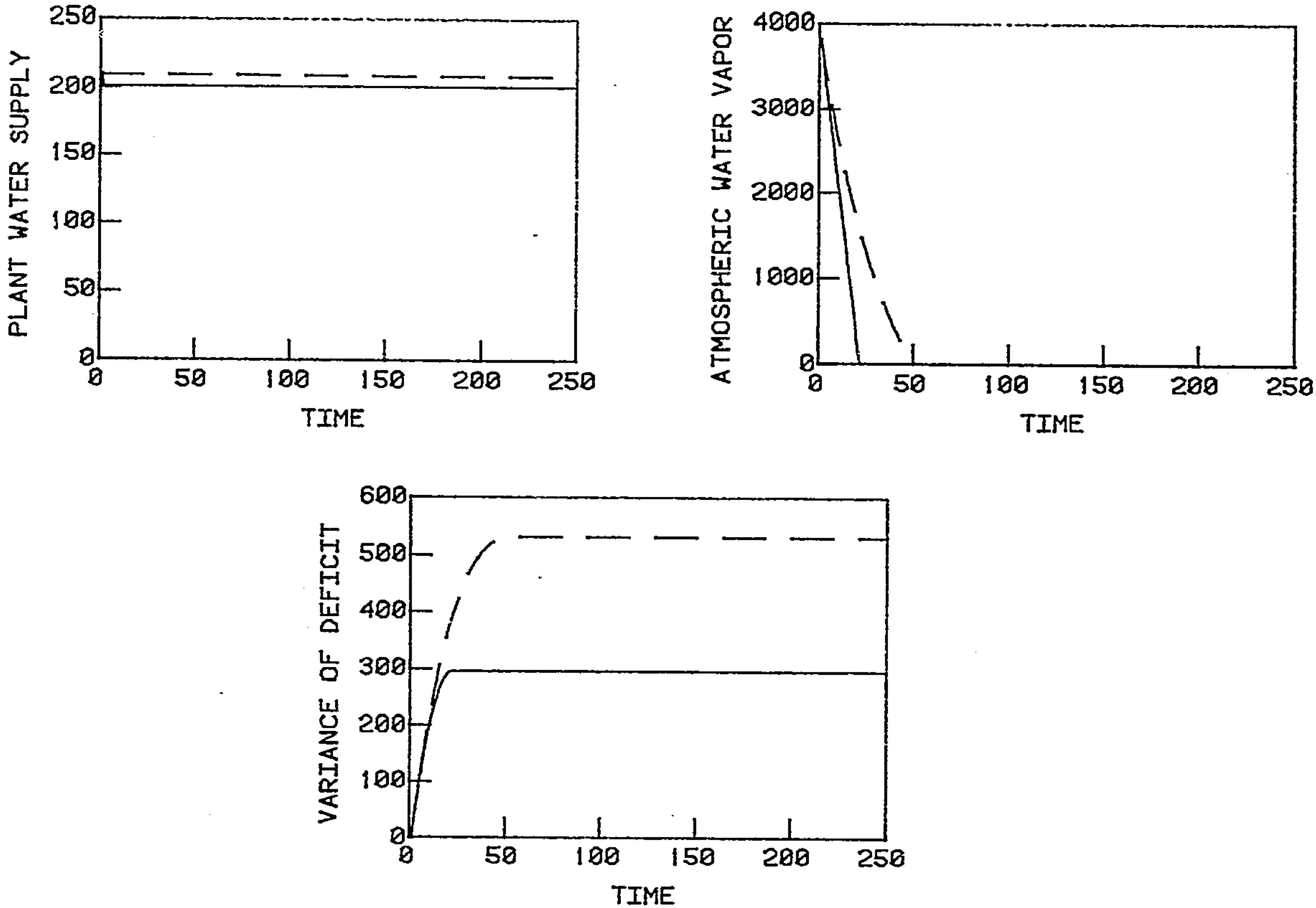


FIGURE 6 OPTIMAL VS. NONOPTIMAL CONTROL WITH NO DISTURBANCE

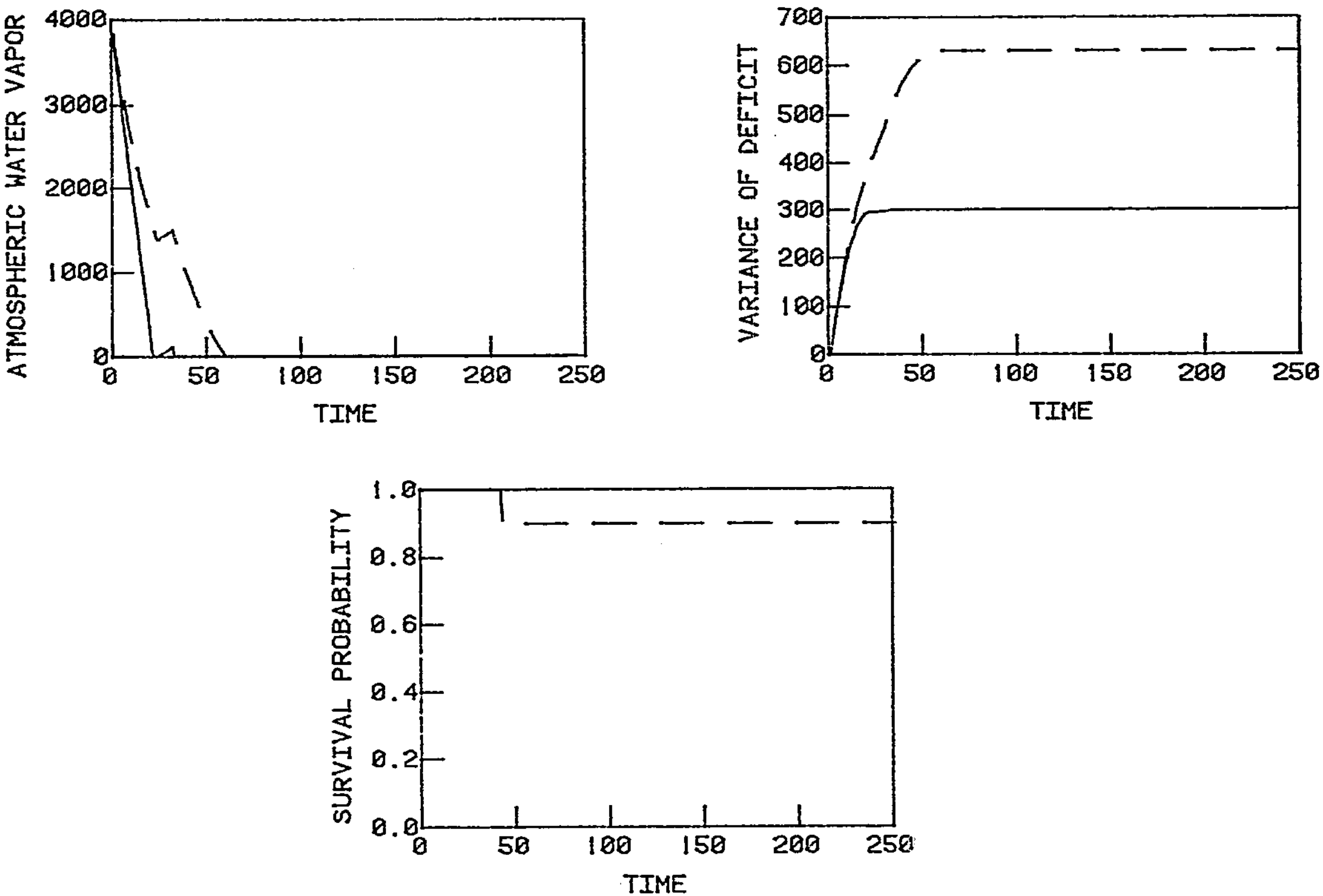


FIGURE 7 OPTIMAL AND NONOPTIMAL CONTROLS WITH DEHUMIDIFIER FAILURE

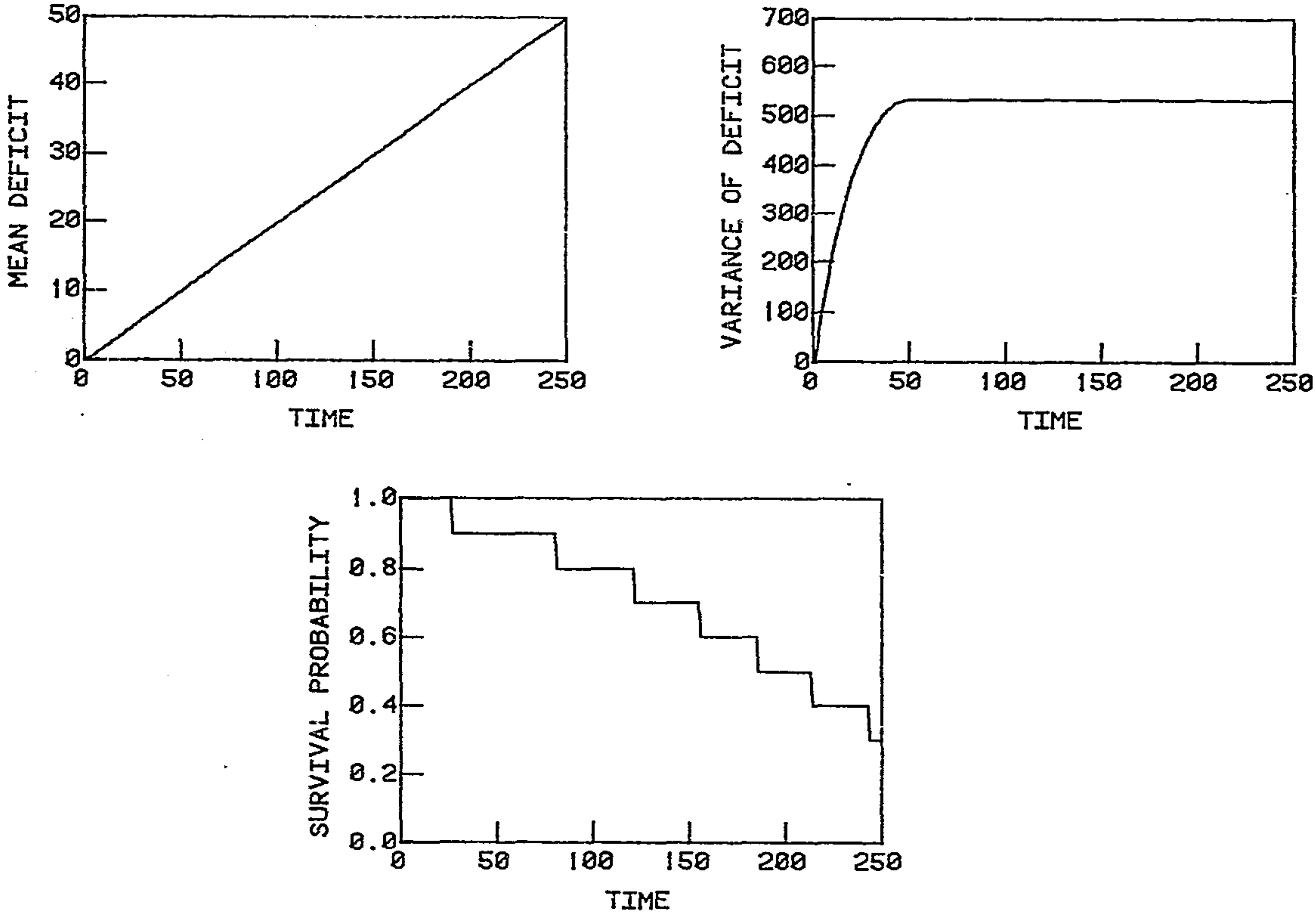


FIGURE 8 NONOPTIMAL CONTROL WITH ERROR IN BASELINE DEMAND

The maximum tolerable error in the baseline demand depends strongly on the number of time steps, N, that we require the system to survive for. Figure 9 shows the tolerable error to guarantee success as a solid line and the minimum error for which failure is guaranteed as a dashed line for various values of N. In general, we would like to make N arbitrarily large; these results imply that to do so requires essentially perfect knowledge of the baseline demand if survival is to be guaranteed using the nonoptimal control.

The optimal control, however, is capable of handling a much larger error in the average baseline demand while still guaranteeing survival. For example, the results of assuming a baseline demand of 2.0 (an 84% error) are shown in Figure 10. Even with such a large error, a steady state with ensured survival is reached rapidly. Indeed the system can still survive the additional disturbance of a dehumidifier failure identical to that described above as shown in Figure 11. Note also that the optimal control keeps the mean deficit at a constant value equal to the error in the baseline demand as long as doing so is consistent with the control saturation limits; this has the effect of making the tolerable error practically independent of the number of time steps for which survival is required. Consequently, N can be made arbitrarily large without a prohibitive increase in system sensitivity.

RESEARCH TASKS

Investigation of resource allocation for CELSS control can be divided into CELSS-specific problems and generic problems associated with

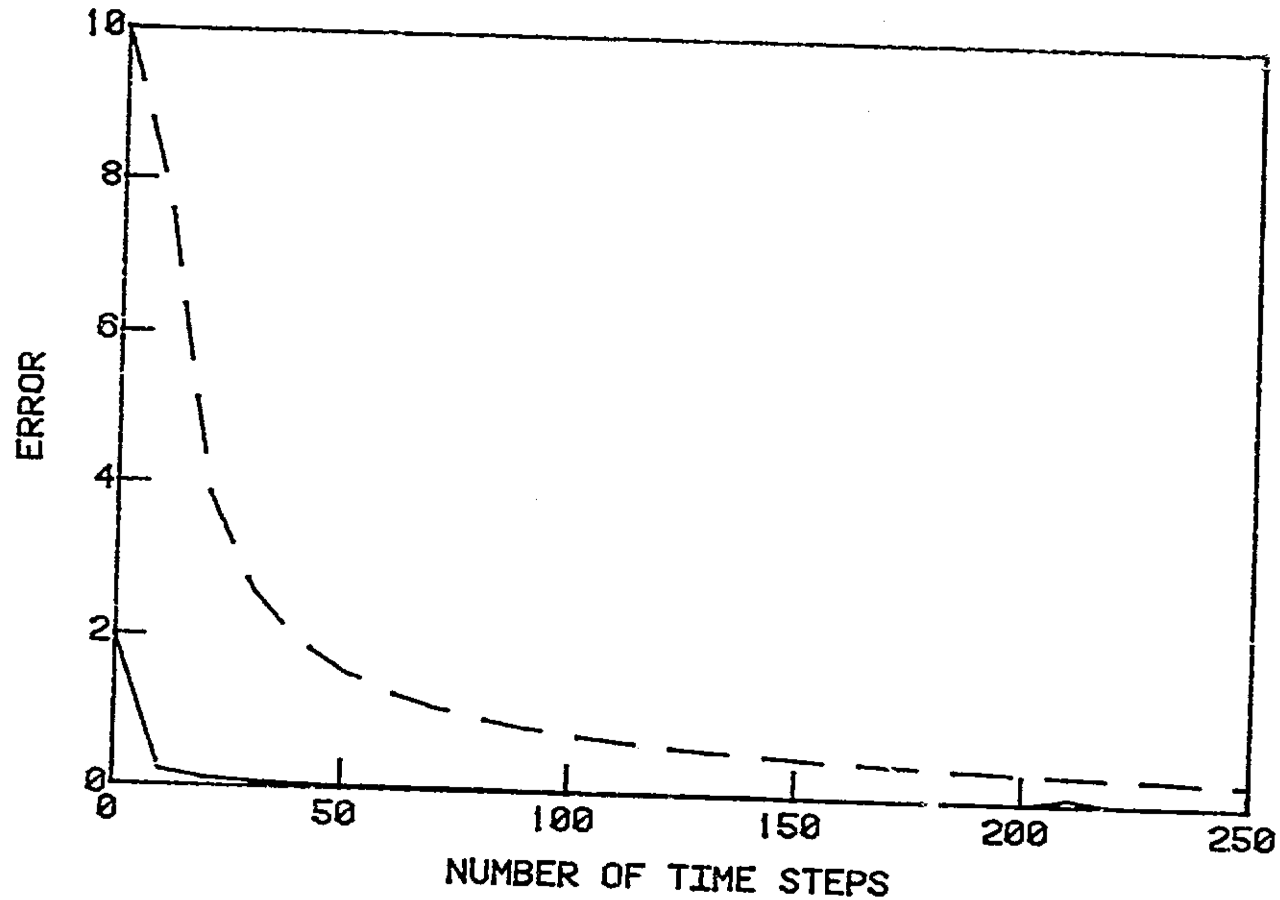


FIGURE 9 SURVIVAL TIME WITH NONOPTIMAL CONTROL FOR VARIOUS BASELINE ERRORS

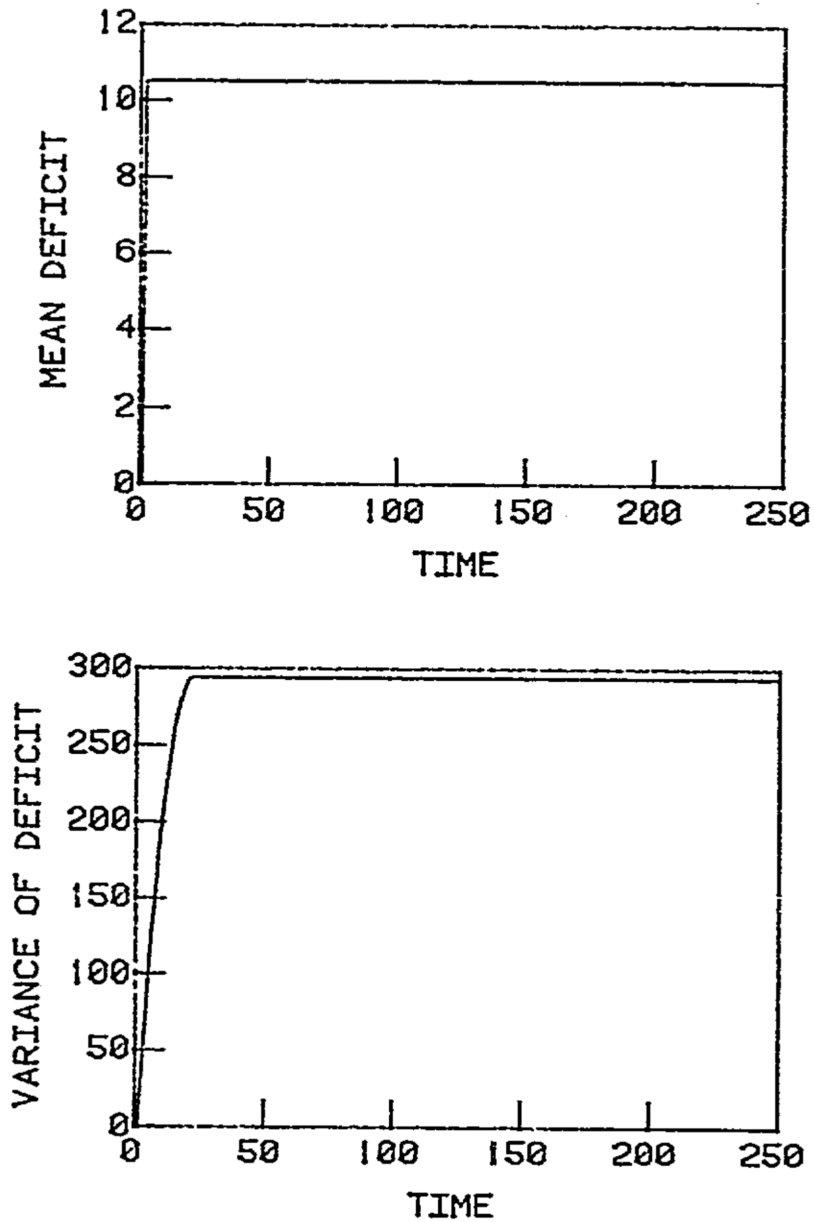


FIGURE 10 OPTIMAL CONTROL WITH BASELINE ERROR

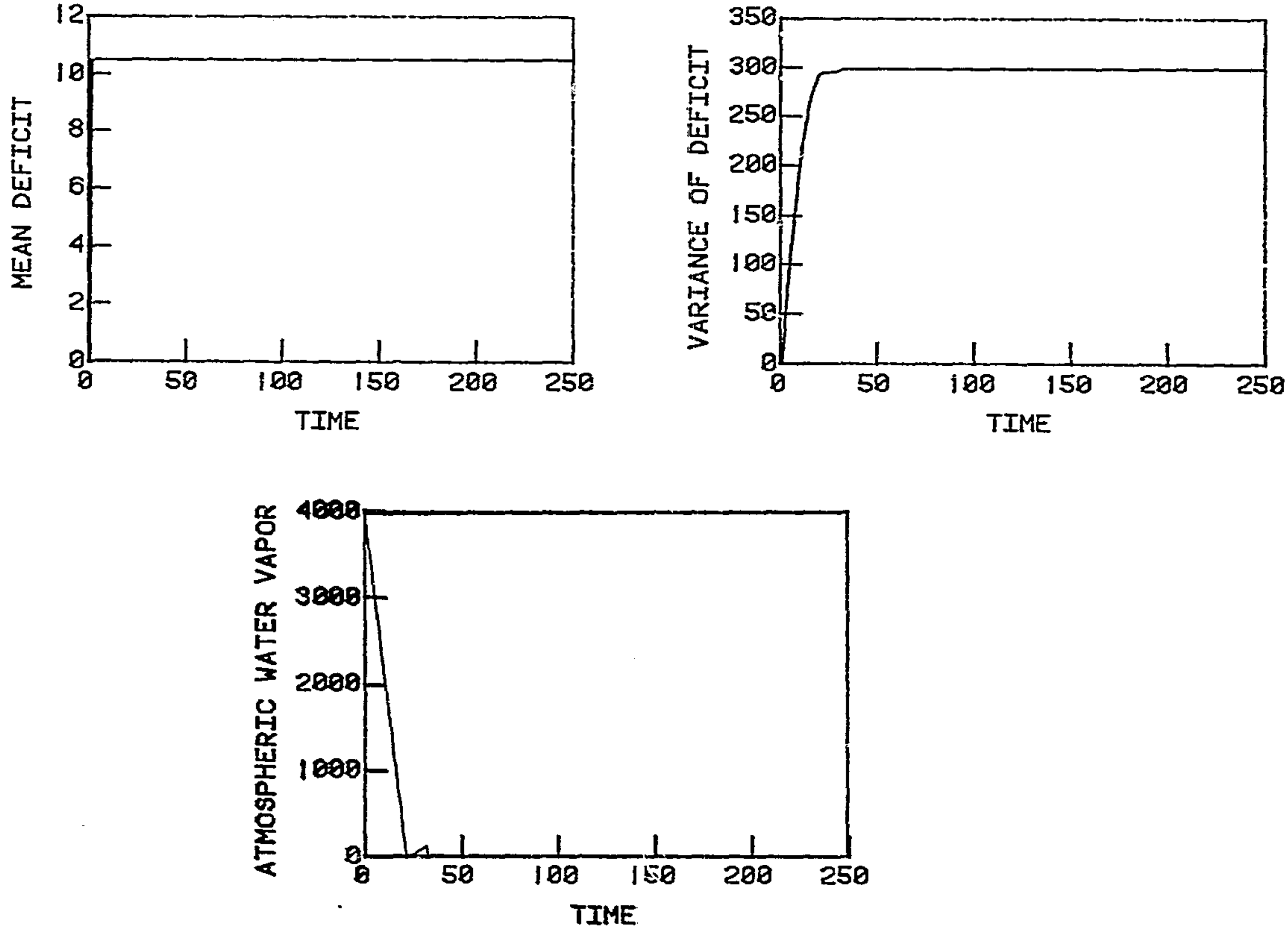


FIGURE 11 OPTIMAL CONTROL WITH BASELINE ERROR AND DEHUMIDIFIER FAILURE

multiple time scales and the dynamic programming formulation. These two areas are not completely independent and most problems to be studied involve a combination of them.

The CELSS model presented in the example above featured only one resource and interactions on only one time scale. In general we cannot exert controls on all dynamic scales; for example we cannot manipulate how much air is inhaled by humans with each breath. While we can control the atmospheric composition by adjusting plant biomass and recycler operation rates, these two controls act on slower time scales than breathing does. Since survival depends on oxygen consumption, which varies on the faster time scale, we must investigate whether or not control on the slower time scale will be adequate to ensure survival.

Another practical problem arises from the dynamic programming formulation. The solution gives the optimal controls as functions of the state vector, requiring the entire state to be known at each time step. However, the model formulation includes deficits (or statistical properties of deficits) and internal supplies of resources as state variables, none of which can be measured directly. Therefore, estimators must be designed to provide approximations of the values of the unmeasurable states.

Because of uncertainties in the model, it is desirable to update parameter values as new information on the system behavior becomes available. If we have a better model, we can presumably obtain a better control. Development of adaptive control schemes may be difficult within the resource

allocation framework because dynamic programming computes the control from a (fixed) final time. If it is necessary to continually recalculate the control sequence starting from final time, the computational load may become prohibitive. Therefore, methods of incorporationg adaptation without significantly increasing the computational load should be studied.

The high computational load is also an important issue in obtaining controls for high order systems. The "curse of dimensionality" (Bellman and Dreyfus 1962) comes about because of the state-space quantization required to apply dynamic programming. Means of increasing the quantization step (i.e. reducing the number of points in state-space used) should be studied; nonlinear quantization may be useful. Sensitivity analysis can be helpful to determine discretization steps for nonlinear quantization, with the smallest steps being in the regions of state-space where the optimal control and cost change the most. Another possibility is approximation in policy space rather than state-space; this would require extending the technique developed by Howard (1960) to the case of time-varying transition probabilities.

The specific research tasks to be accomplished are:

a)Select specific CELSS models with several resources and multiple time scales.

b)Investigate effect of control on slow time scales with performance indices dependent on fast time scale dynamics.

c)Identify available measurements and design estimators to approximate unobtainable states.

d)Investigate methods of including adaptation in the controller and estimator designs.

e)Determine best state-space discretization to reduce computational load.

f)Investigate approximations in policy space with time-varying transition probabilities.

<u>Control of Systems with Delay and Closure</u>

It is possible to gain insight into the dynamic behavior of a CELSS through the use of simple abstract models of its fundamental components. Here, we present two such models to demonstrate the complex system behavior that can arise from simple models whose primary characteristic is a time delay. The first abstract model is one representing the basic features of plant growth. The second model is based on the ideas of mass closure and a finite ability to store resources.

A CELSS that contains plant growth will have a component that is characterized by a long delay. This delay represents the time between planting and harvest. During this time the plant growth rate, and therefore the harvest yield, is affected by the local environment. Local influences can arise from the temperature, carbon dioxide level, nutrient level, water available for transpiration, etc. (Averner, 1981). We will lump all of these disturbances, both positive and negative, into a single random term which contains the plant growth uncertainty. Therefore, the abstract model of plant growth contains a simple time delay and a gain that has a random component.

This model permits investigations into the dynamic consequences of a system that contains the essence of the complex transition from seed to harvest. Further, the model permits the investigation into the consequences of various schemes that can be used to increase the reliability of the harvest. Two such schemes, control and storage use, are presented below.

A second abstract model is constructed to examine the effects of mass closure with finite storage in a system with a long delay. The choices of what to do with a resource are limited by the mass closure. At no time are we permitted to discard excess material. The minimization of storage tank size is necessary for the CELSS to be cost effective for a mission (Gustan and Vinopal, 1982). Therefore, it is possible that a situation will occur when a resource has been processed but its storage tank is full. In this case, the resource will have to be put in an undesirable place. This introduces a multi-valued nonlinearity into the system: having more of a resource is better only up to a point; then it becomes detrimental to the system.

Our second abstract model permits investigations into the consequences of overloading a storage tank in the processing loop. This model contains a time delay that represents the processing time associated with various components in the CELSS. A nonlinear gain is also included to model the penalty associated with a filled storage tank. Although this model uses deterministic inputs, the combination of the delay and nonlinear term lead to cyclic and apparently random behavior. It is of particular interest

to the CELSS problem that a simple, deterministic system, characterized only by a time delay and storage limitations, can generate complex behavior.

AN ABSTRACT MODEL OF PLANT GROWTH

Consider an abstract model of plant growth where there is a delay of T units (constant) between planting and harvest. The growth during this time is random:

GROWTH = 1 +/- 20%

This model is shown schematically in Figure 12. The units for harvest and seeds planted are normalized so that one unit of seeds corresponds to one unit harvested, on the average. The random growth term represents the uncertain effects of the environment on the plant growth.

A deficit will be defined here as the accumulation of:

FOOD NEEDED - HARVEST when: FOOD NEEDED > HARVEST. A value of 10 units will be used for the FOOD NEEDED in this model.

Figure 13a shows the harvest (output) of such a system where enough seeds are planted to insure that the harvest equals the food needed when the average growth rate is in effect. The associated deficit is shown in Figure 13b. This is referred to as an uncontrolled or open-loop system.

If it is desirable to reduce the fluctuations of the harvest, and therefore the accumulation of the deficit, either storage, control, or excessive planting must be added to the system. Extra planting is not

Figure 12: Abstract Model of Plant Growth

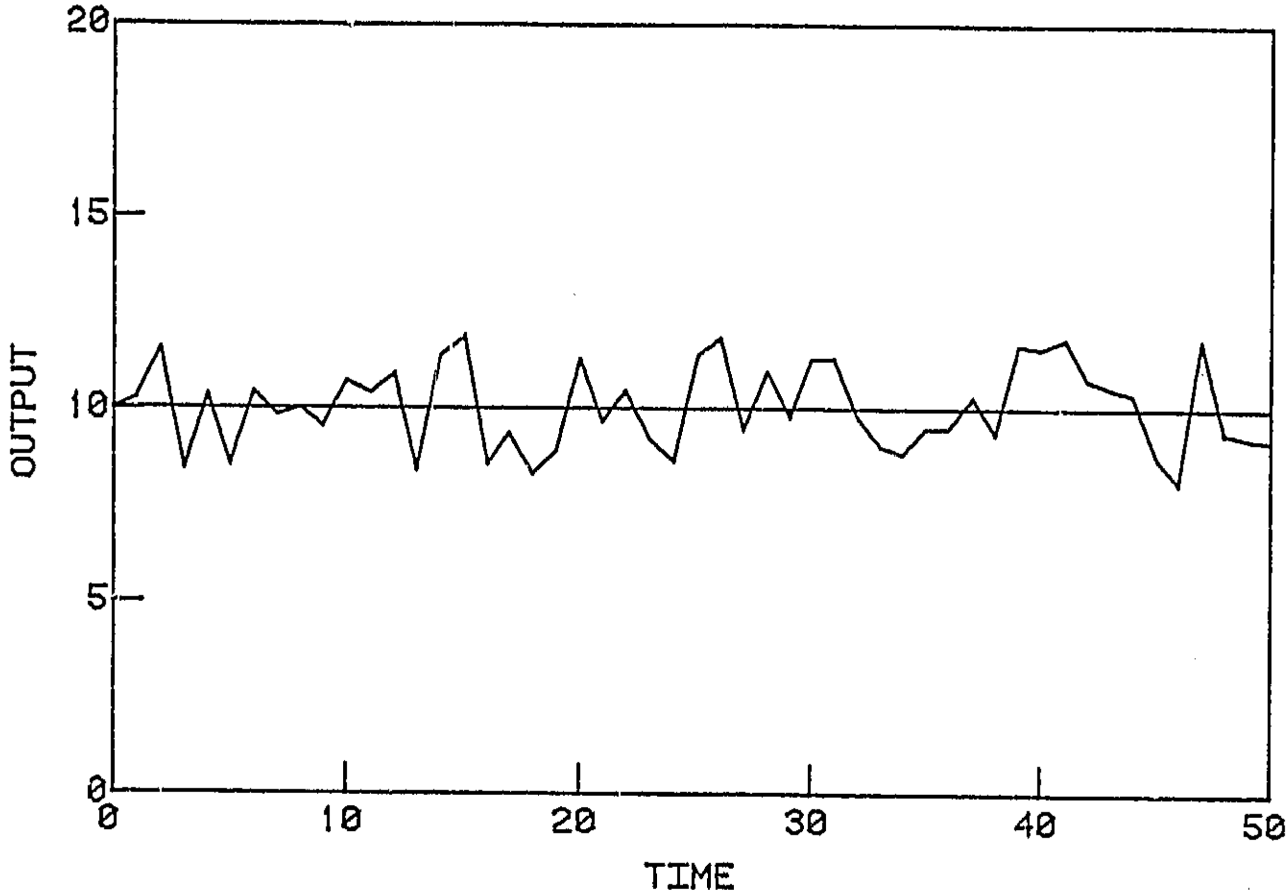


Figure 13a: Harvest of Uncontrolled System

(Food Needed = 10)

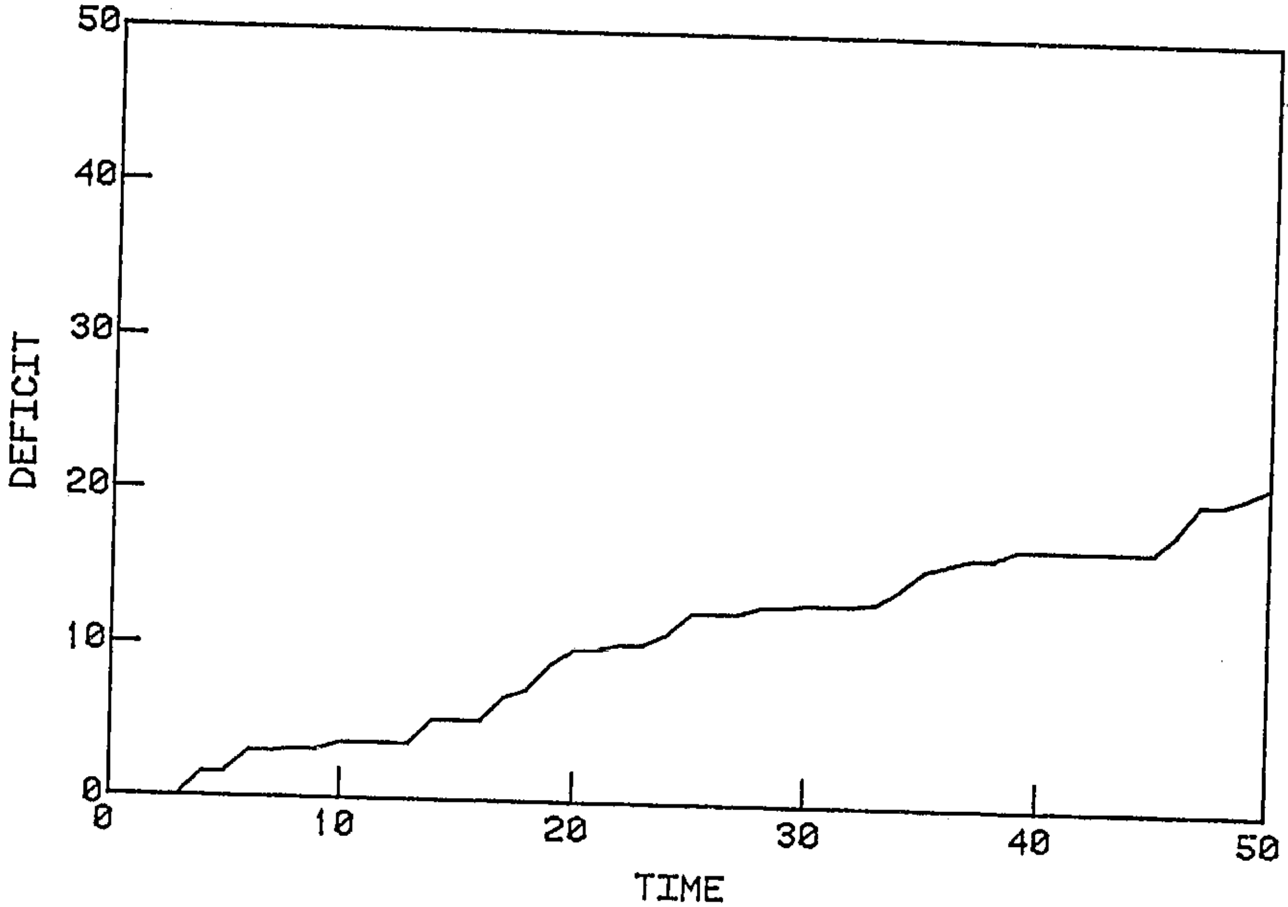


Figure 13b: Accumulated Deficit of Uncontrolled System

wise because of the burden on system resources and the required increase in system volume. Therefore, we will investigate the potential benefits of control and storage on the system behavior.

A control could be applied to the system to gain greater reliability and lower total deficit. First, consider a heuristic control where the current amount of seeds planted depends on the current harvest. This scheme, which closes the loop through feedback of the system output, is shown in Figure 14. The harvest is compared with the food needed. The correction, or adjustment, to the seeds planted is determined by the user set sensitivity to the comparison between the harvest and food needed. As an example of the difficulties that can arise in dynamic systems, our first example of control will use a sensitivity value of 1. Although this value seems like a reasonable first guess (see example in Figure 14), the results shown in Figures 15a and 15b show that the system behavior has deteriorated. Further, the noise band of the harvest has increased from +/- 20% to +/- 80%.

Clearly this control does not improve the system performance, which is not surprising when the transfer function of the system in Figure 14 is examined:

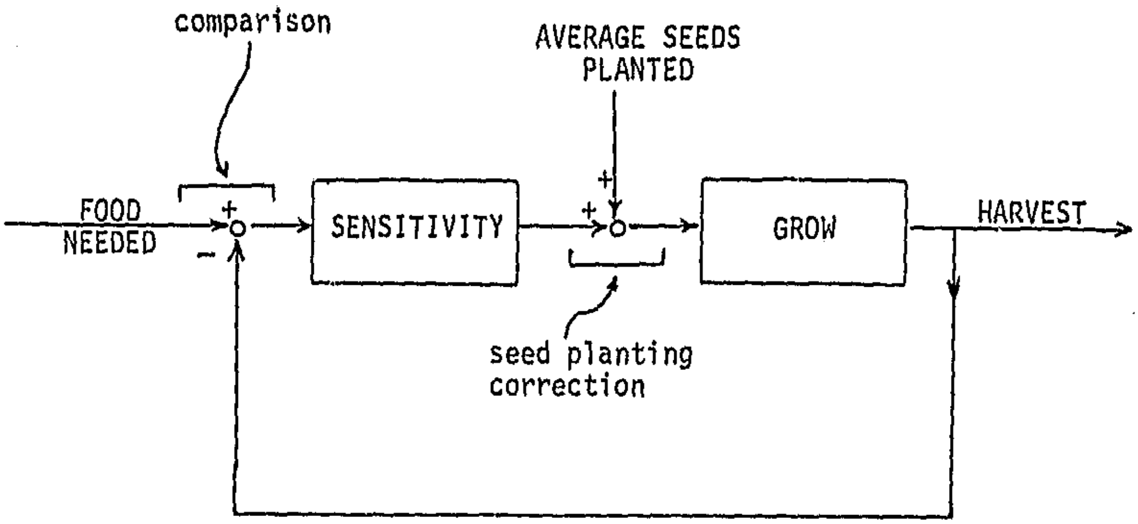
$$Y(z)/R(z) = [\ G(K + 1)\ ] \ / \ [z + GK]$$

where: $Y(z)$ = transform of the harvest

$R(z)$ = transform of the set point (food needed)

G = growth rate of plants

K = control gain (sensitivity)



Example:

Food Needed = 10	→	Seed Planting Correction = 2
Harvest = 8		Seeds Planted = 12
Sensitivity = 1		

Figure 14: Heuristic Control Using Output Feedback

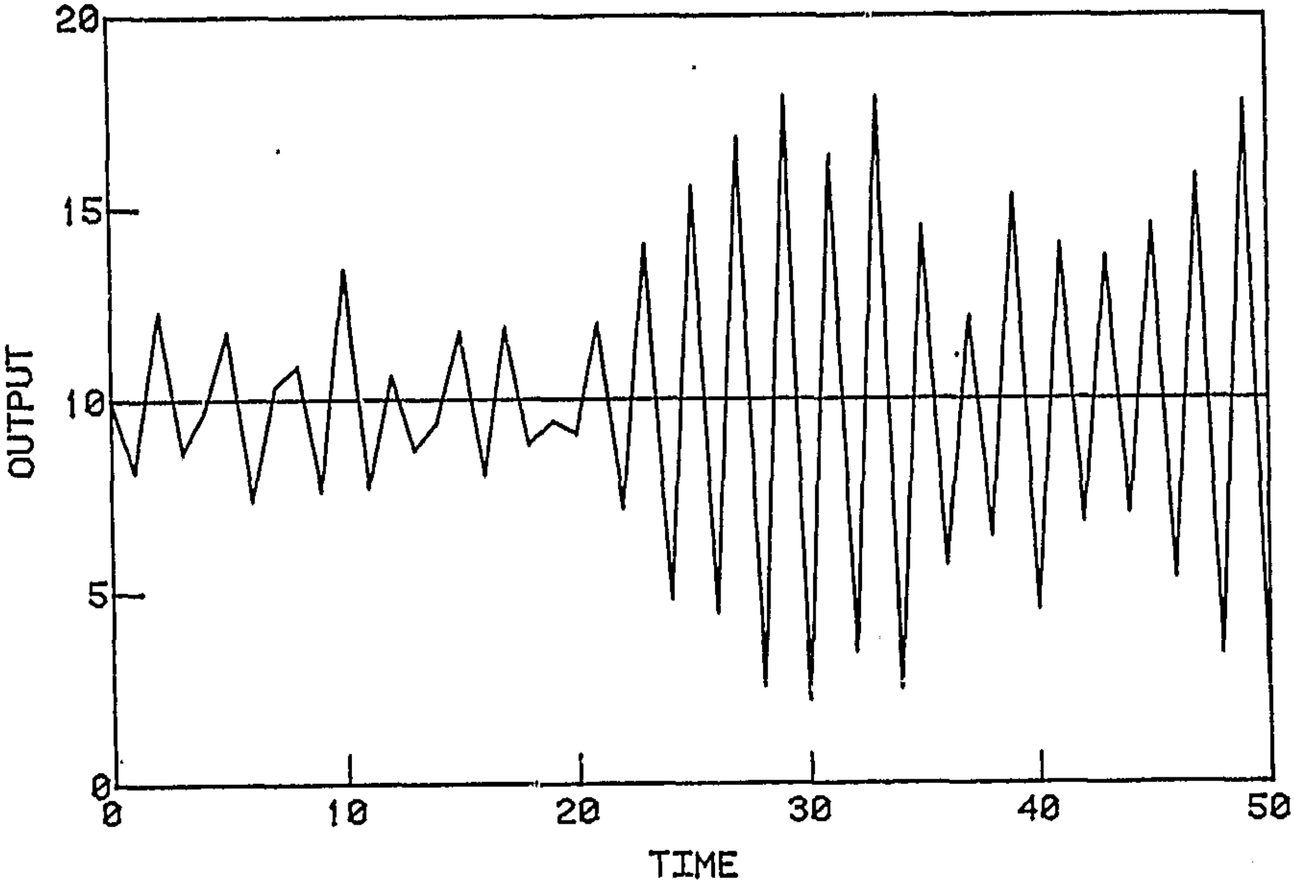


Figure 15a: Harvest of System with Output Feedback Control
(Sensitivity = 1)

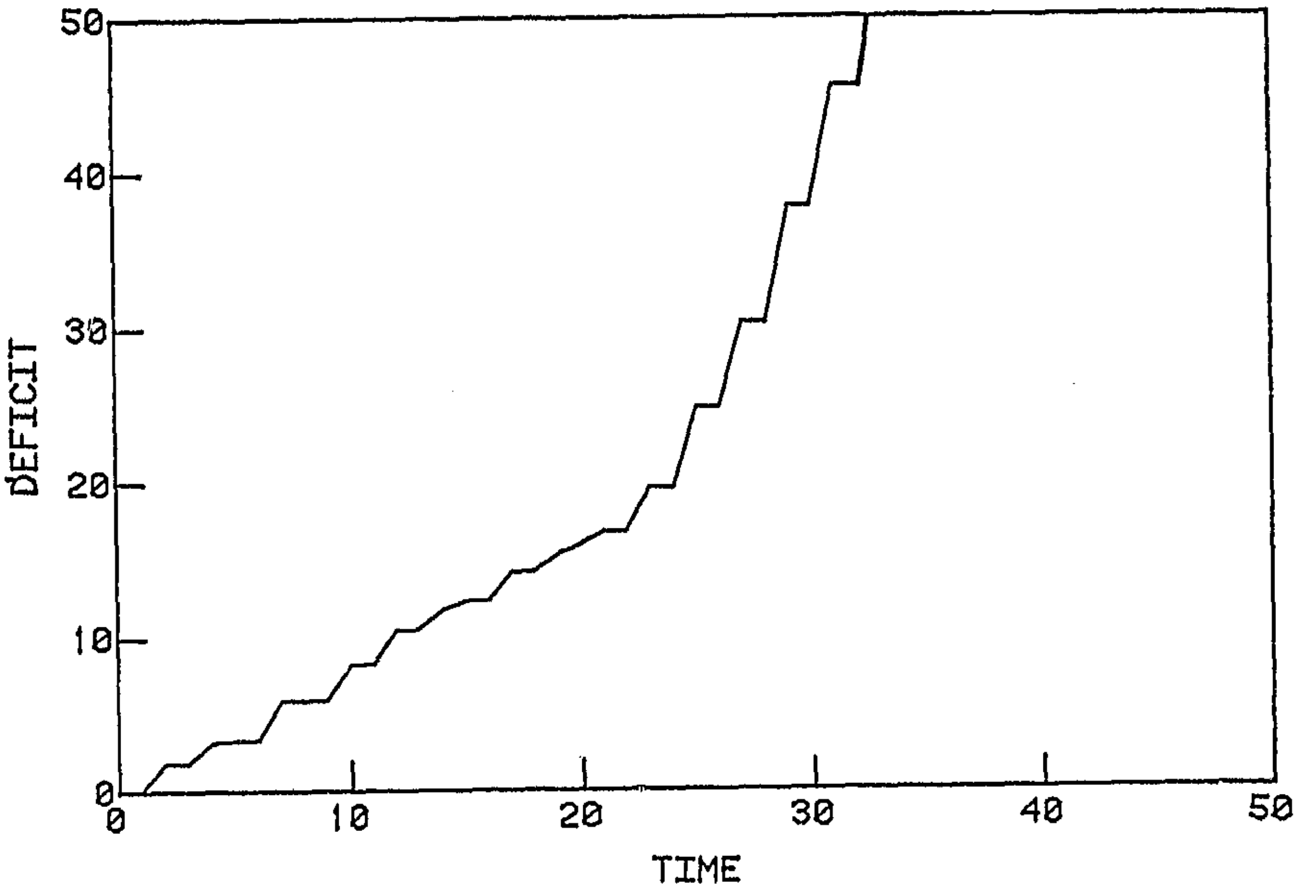


Figure 15b: Accumulated Deficit of System with Output Feedback Control

The stability criteria for this system is:

$$K < 1/G$$

Therefore, the use of a sensitivity (K) of 1 is unstable when the plant growth is greater than 1. The instability is reflected in the increasing fluctuations of the harvest in Figure 15a. Stability would be maintained with values of K less than (1 / 0.8).

The output control of Figure 14 achieved its best results with a sensitivity of 0.1. However, the accumulated deficit with this control was no lower than the case with no control. Other variations of output control are possible. The control presented in Figure 14 is a proportional or P control. The adjustment to the number of seeds planted is proportional to the error between the harvest and the food needed. An accumulation of these errors could be used to determine the seed planting adjustment. This control, integral or I control, also did not improve the overall system behavior. Finally, a combination of the P and I control was applied. The results with this PI control are shown in Figures 16a and 16b. It can be seen that the use of this output control also does not improve the system reliability or reduce the accumulated deficit.

A controller which uses information during the delay period is needed to improve the system performance. State variable feedback control adjusts the system input based on observations taken during the delay. Such a system is shown in Figure 17. Figures 18a and 18b show the harvest and deficit for a system with a controller that uses information from 10 observations during the time the plant is growing. State feedback improves

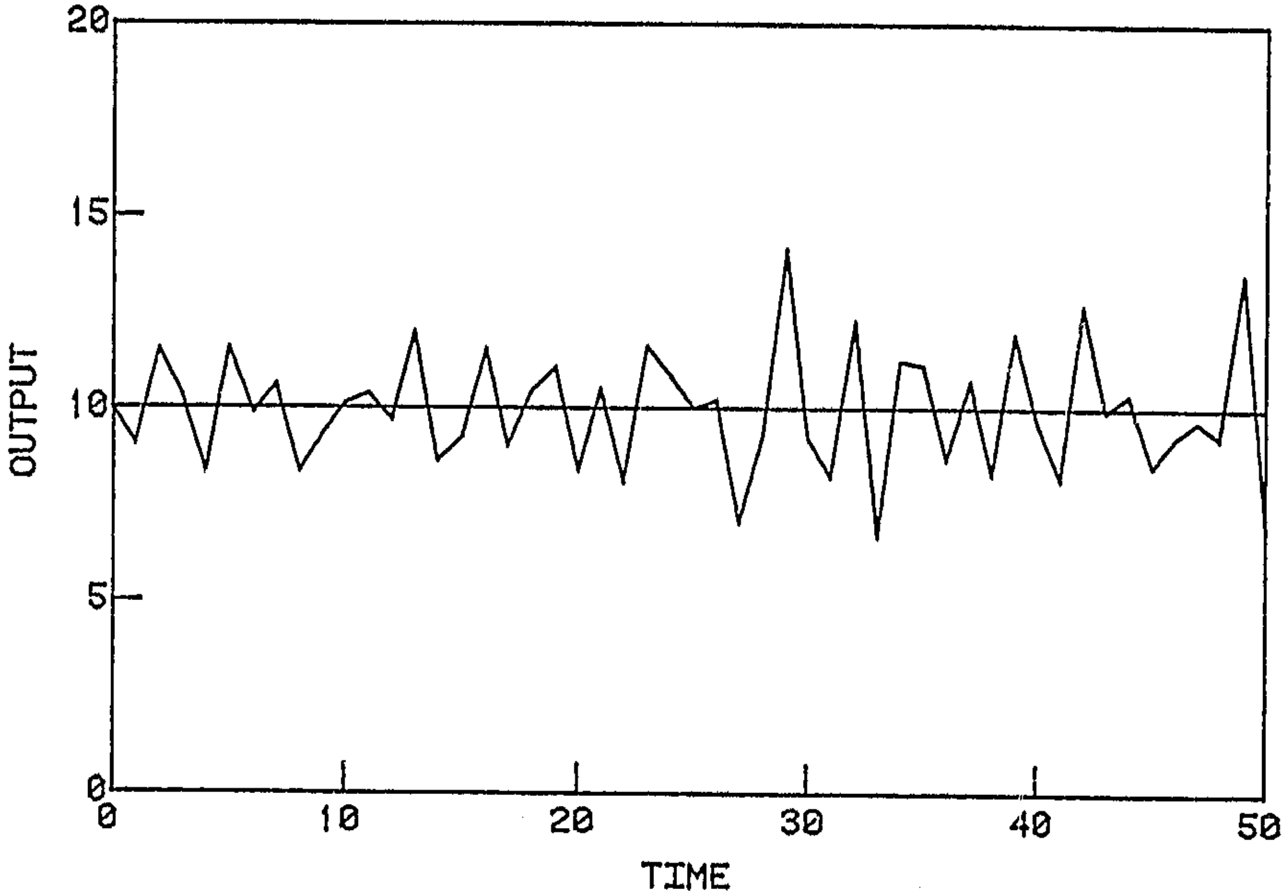


Figure 16a: Harvest of System with PI Output Feedback Control

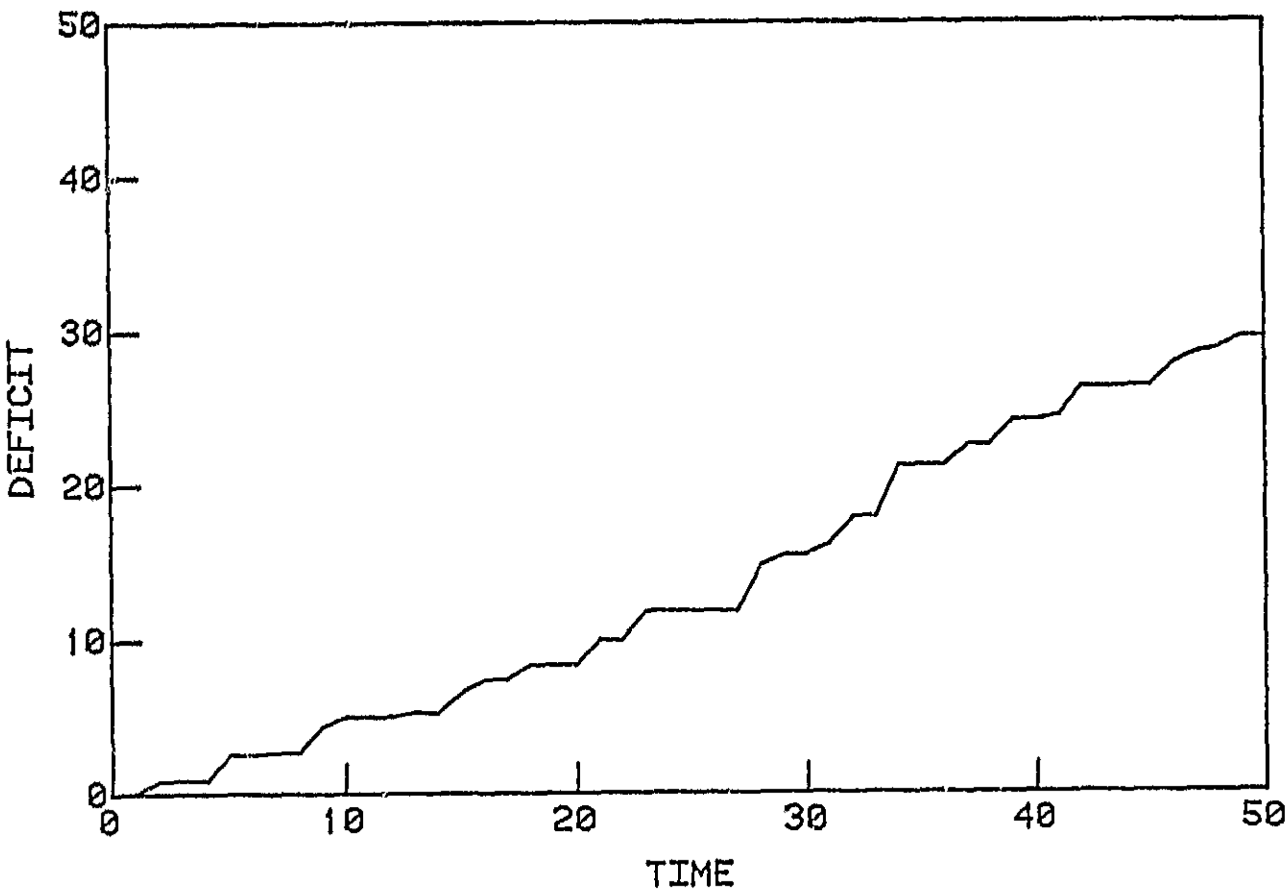


Figure 16b: Accumulated Deficit of System with PI Output Feedback Control

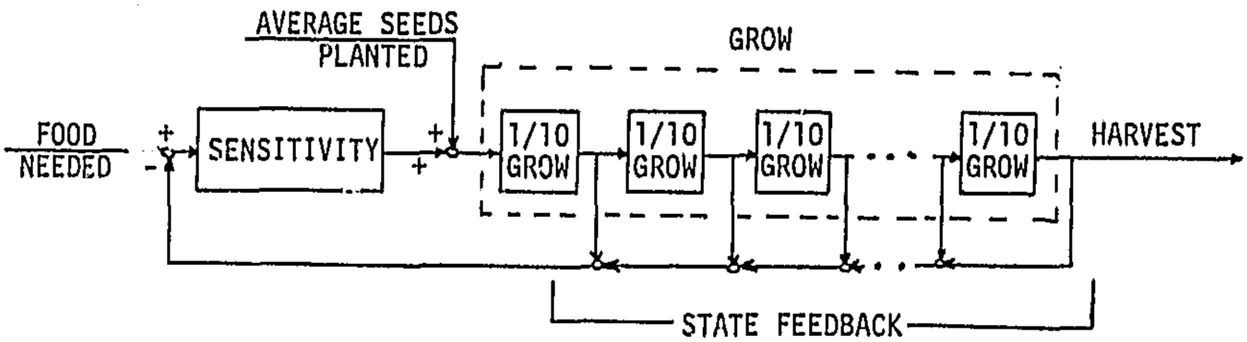


Figure 17: System with State Feedback

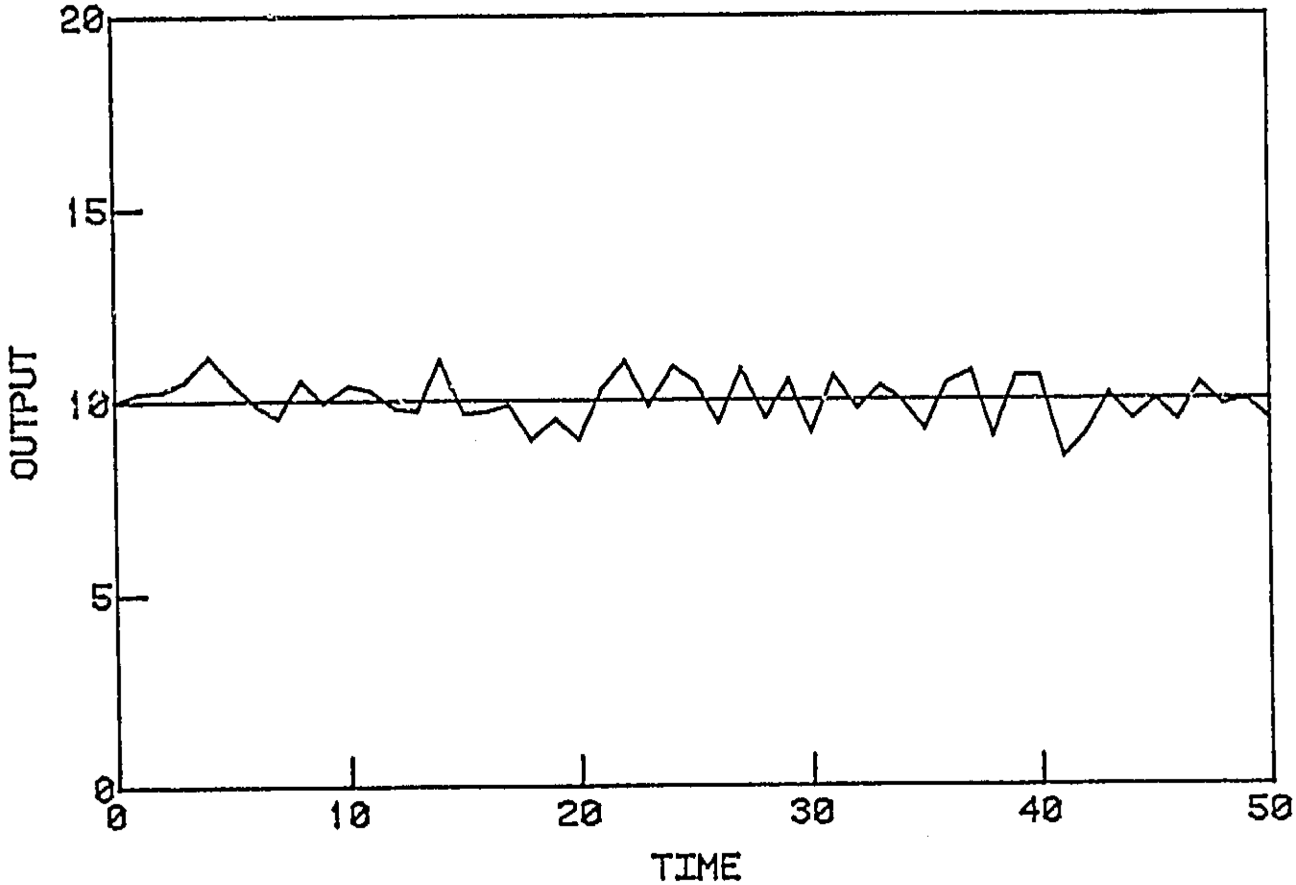


Figure 18a: Harvest of System with State Feedback Control

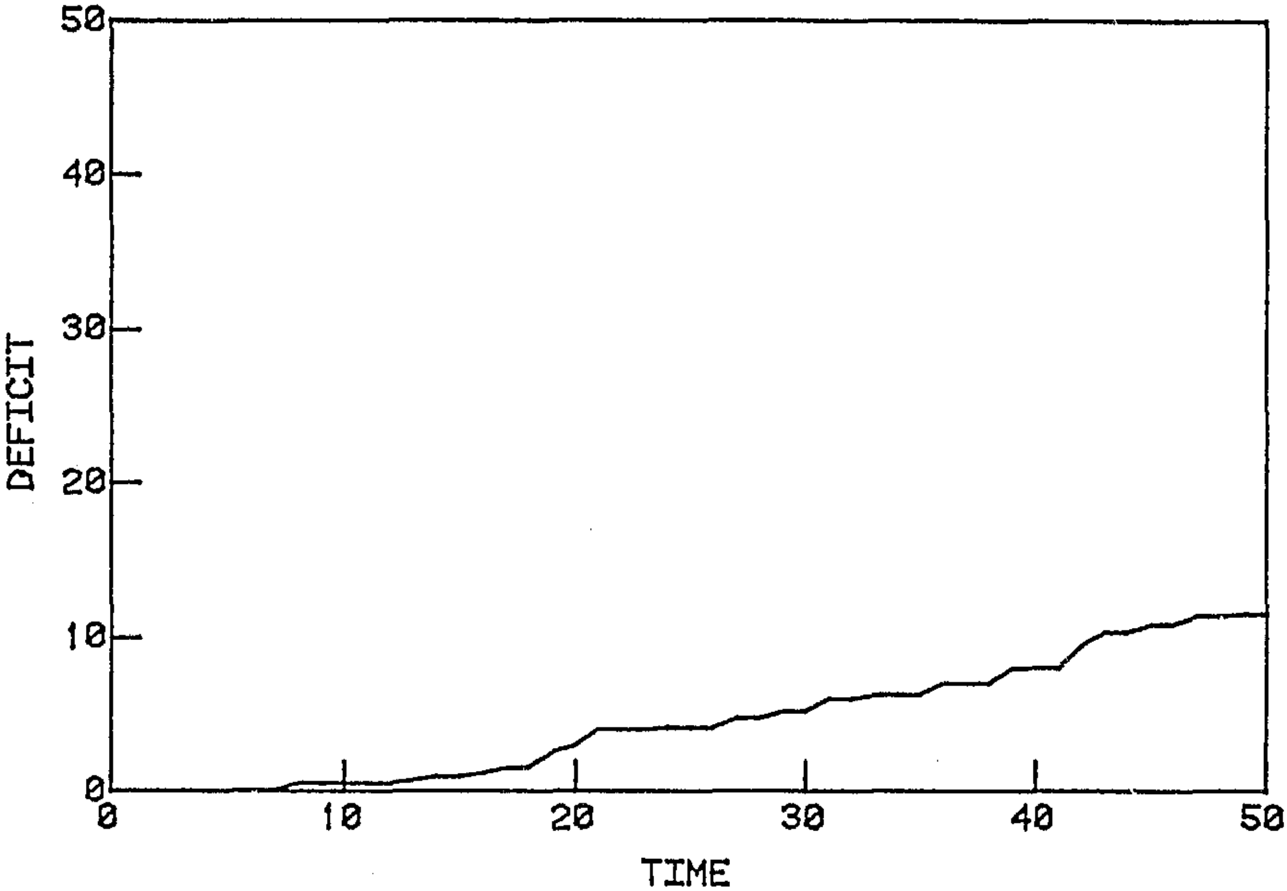


Figure 18b: Accumulated Deficit of System with State Feedback Control

the system performance and reliability over the uncontrolled situation.

We now consider the use of a food storage tank as a possible means of improving the system behavior. An adequately large storage tank can insure that for a statically balanced system, the uncontrolled system never has a deficit (Figure 19). This storage tank does have a penalty associated with it: extra mass, volume, etc. The use of storage does not always insure that there is no deficit, as shown below.

If the plant growth is poorly estimated, or there is a low frequency random disturbance present, then the growth rate may actually be (as an example):

GROWTH = 0.8 +/- 20%

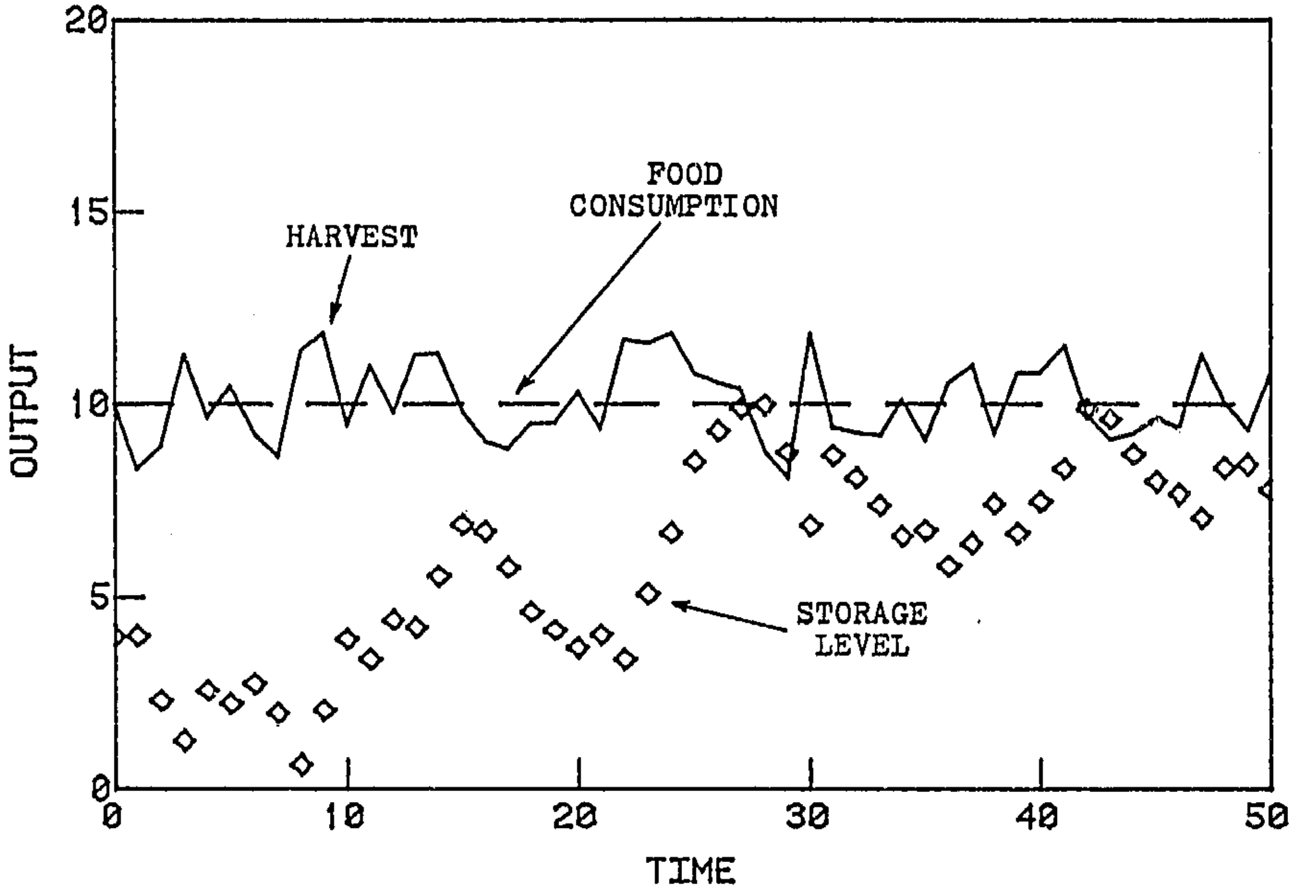
while the system operation is based on the assumed growth:

GROWTH = 1. +/- 20%

In this case the uncontrolled system will quickly empty the storage tank and large deficits will accumulate (Figures 20a and 20b).

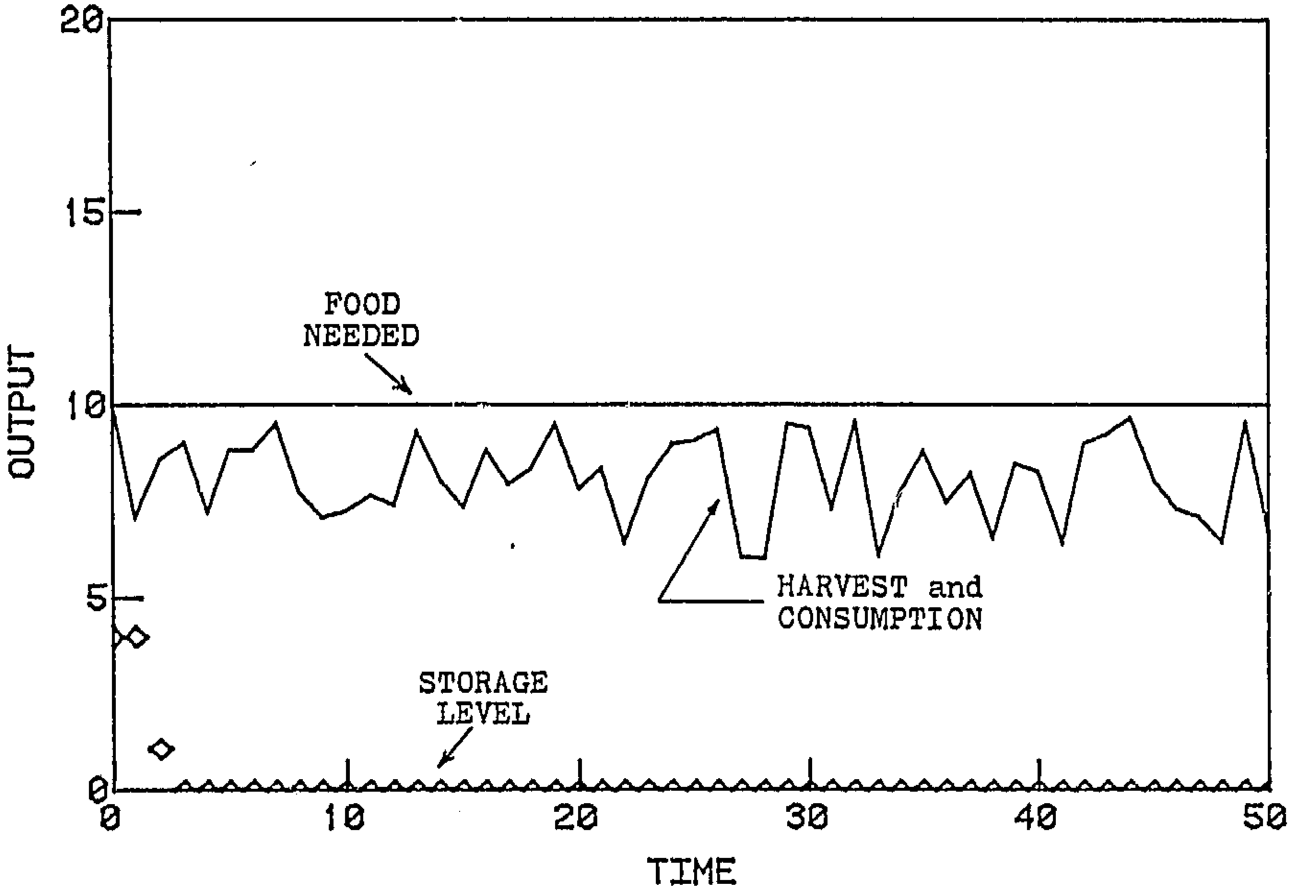
It is possible for a controlled system to maintain low deficits in this poorly estimated system without the use of a storage tank. System performance is improved with the use of a PI output controller. This result, shown in Figures 21a and 21b, is achieved without the use of a storage tank.

A further improvement in the system behavior can be obtained for the case of a poorly estimated growth rate by using a state feedback control (Figures 22a and 22b). In this example also, no storage tank was used.



Note: Since the Food Consumption = Food Needed, the Deficit is always equal to 0.

Figure 19: Harvest, Storage Level, and Food Consumption of Uncontrolled System



Note: Harvest always equals consumption while storage is 0.

Figure 20a: Harvest and Storage Level for Uncontrolled System with Poorly Estimated Plant Growth

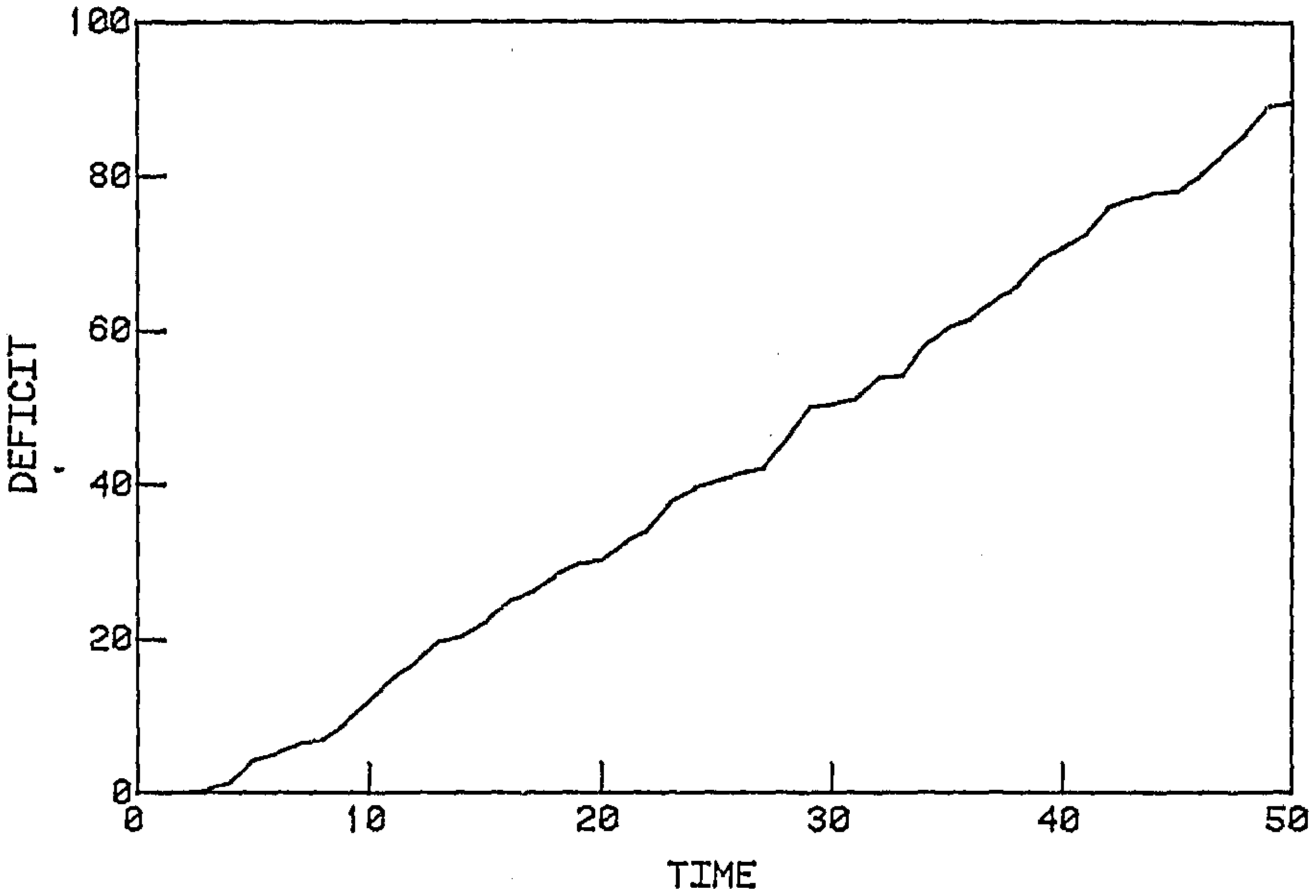


Figure 20b: Accumulated Deficit of Uncontrolled System with Poorly Estimated Plant Growth

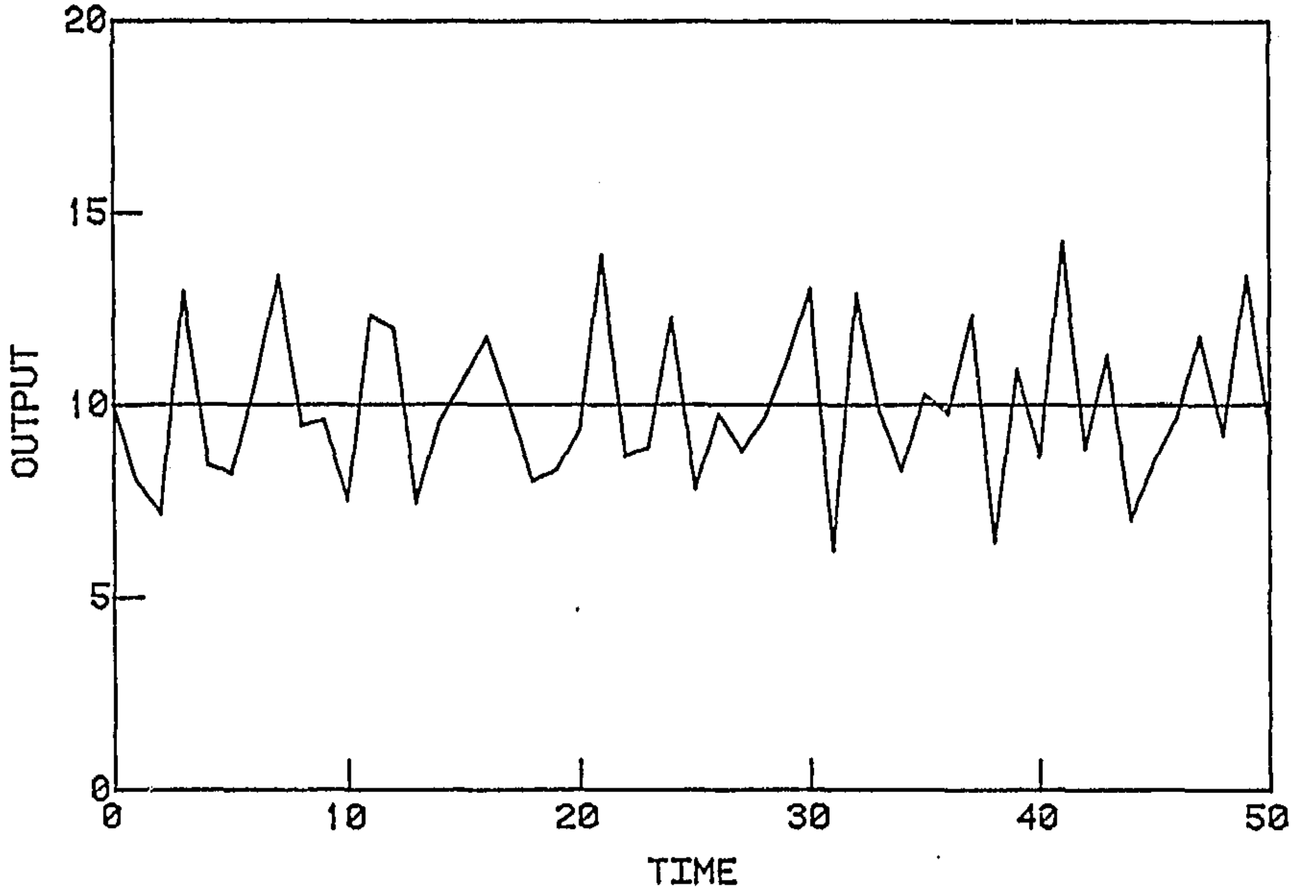


Figure 21a: System with PI Output Feedback Control and Poorly Estimated Plant Growth

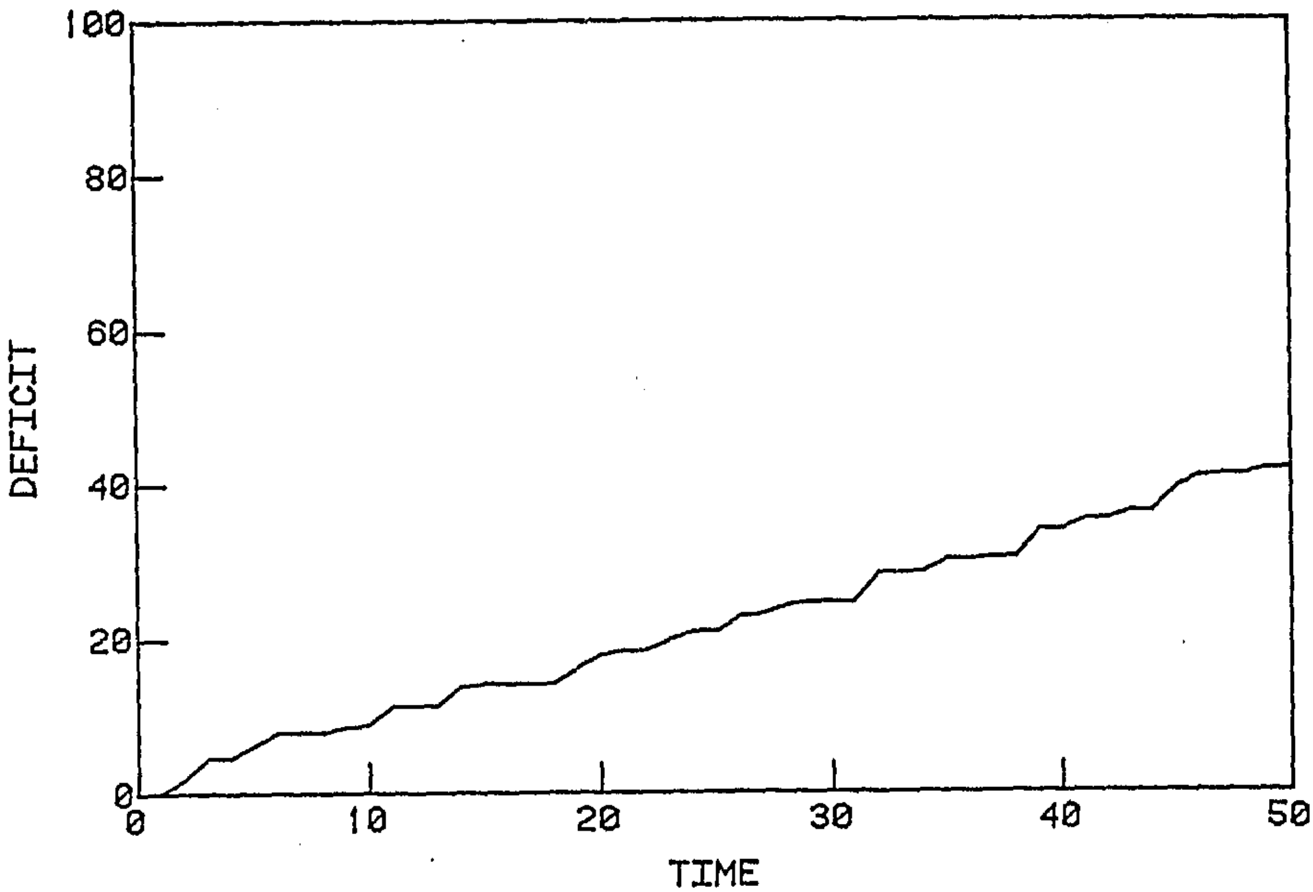


Figure 21b: Accumulated Deficit of System with PI Output Feedback Control and Poorly Estimated Plant Growth

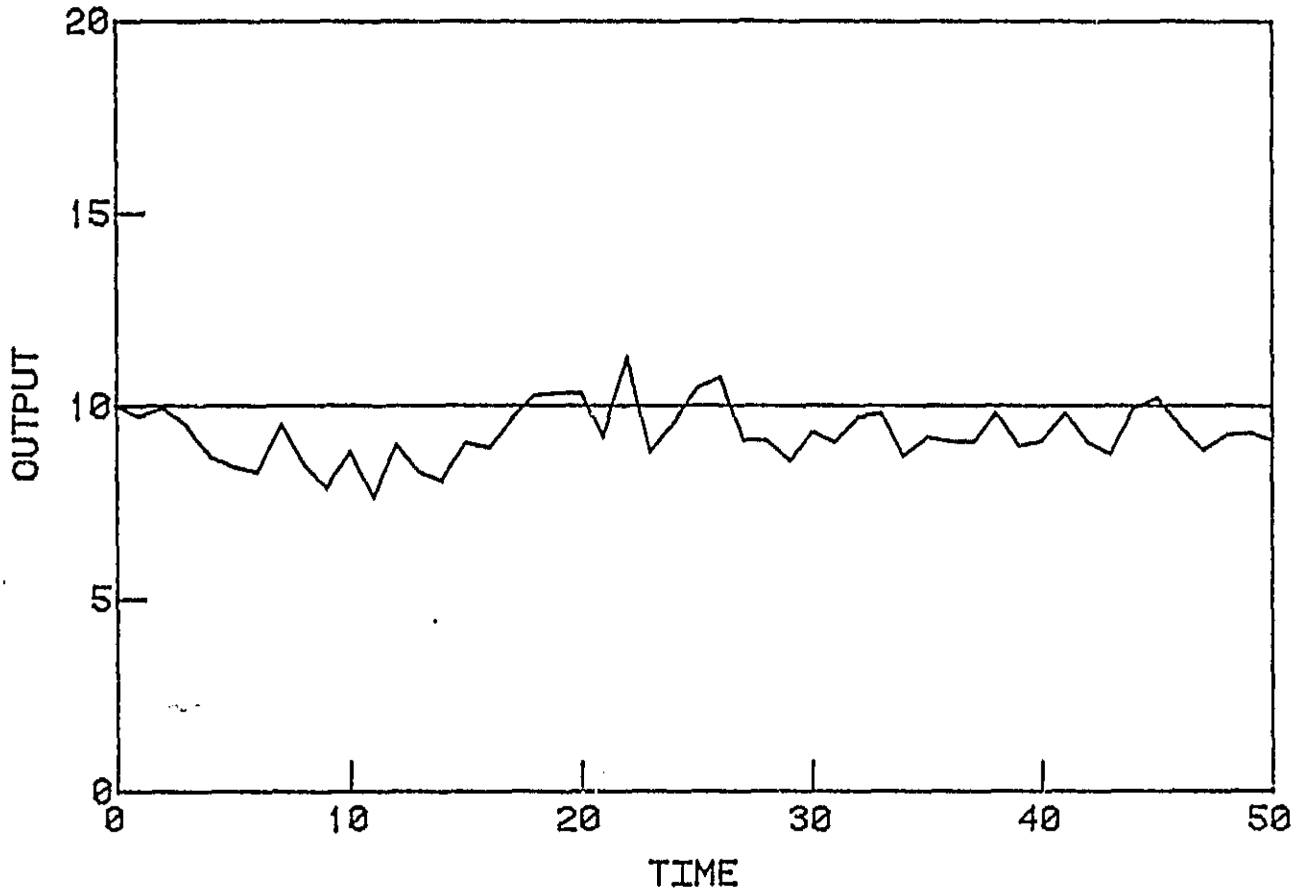


Figure 22a: System with State Feedback Control and Poorly Estimated Plant Growth

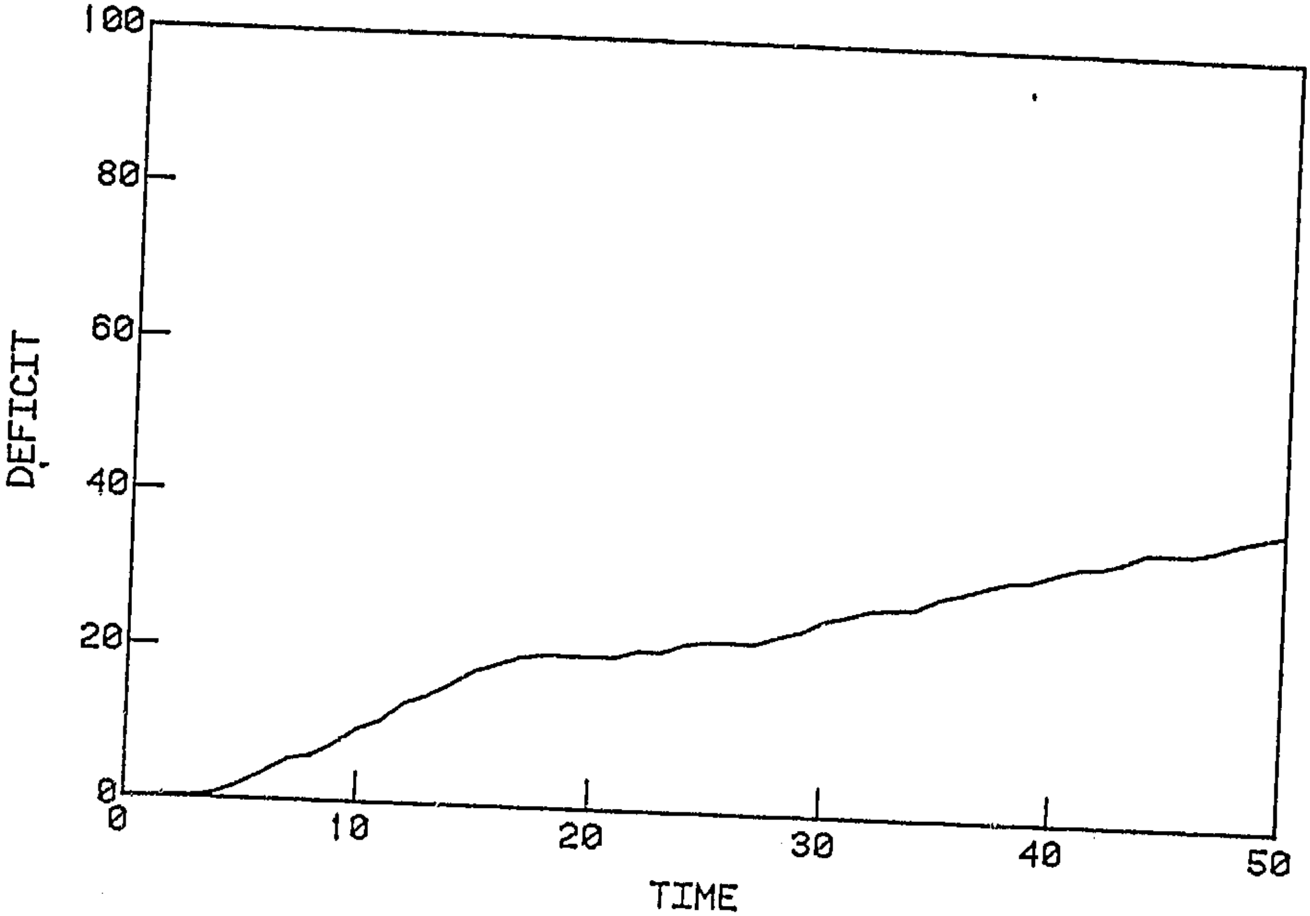


Figure 22b: Accumulated Deficit of System with State Feedback and Poorly Estimated Plant Growth

Systems with delay, even ones as simple as described here, are difficult to control. Heuristic control schemes often can create disastrous results (Figures 15a and 15b). The use of a storage tank improves the system performance when only a high frequency disturbance exists. The storage tank alone is not enough to insure reliability when low frequency disturbances are present. Systems with delay can be controlled with schemes that use observations of the system state during the delay period. These state feedback controllers are effective for a wide frequency range of disturbances and reduce the need for a storage tank. The storage tank is useful, however, for smoothing out the remaining high frequency fluctuations in the harvest.

In this discussion we have only examined a linear system with a simple stochastic component. The use of a state variable feedback controller has been demonstrated, but the techniques of acquiring the many states needed by this control have not been addressed. More sophisticated controllers will be required to deal with the problems of optimization, nonlinearity, and parameter uncertainty.

AN ASTRACT MODEL WITH FINITE STORAGE

Consider an abstract model of a system with mass closure and finite storage. This model could represent one of the many loops that resources follow in a CELSS. In this abstraction we will only be concerned with the effect of this moment's resource level on the next harvest's resource

level. Therefore, this model will contain a delay term that represents the time it takes for the resource to propagate through the loop.

We will hypothesize a relationship between harvest resource levels as:

$$x(t+1) = x(t) \exp[\, r(1 - x(t)) \,]$$

where: $x(t)$ = current resource level

$x(t+1)$ = resource level at next time step

r = functional relationship between harvests

t = integer time that increases in steps of T units

This relationship for various values of r is shown in Figure 23.

The relationship between successive resource levels is characteristic of a system that is resource limited and has a penalty associated with excessive accumulations of a resource. The behavior of this abstract model depends on the value selected for r. When r is less than 2 the system is locally attracting to the point $x = 1$. As r is increased past 2 the system shows periodic limit cycles of increasing complexity and period. When r is greater than 2.71 the period of the oscillations goes to infinity and the system behavior becomes chaotic (May and Oster, 1975). This transition of behavior is shown in Figures 24 through 27.

Chaotic behavior is particularly interesting from the viewpoint of system control. A very simple system with only a time delay and a nonlinear gain is able to generate apparently random behavior even though the system is purely deterministic. We will first examine some of the necessary conditions for this behavior and then will discuss its relationship

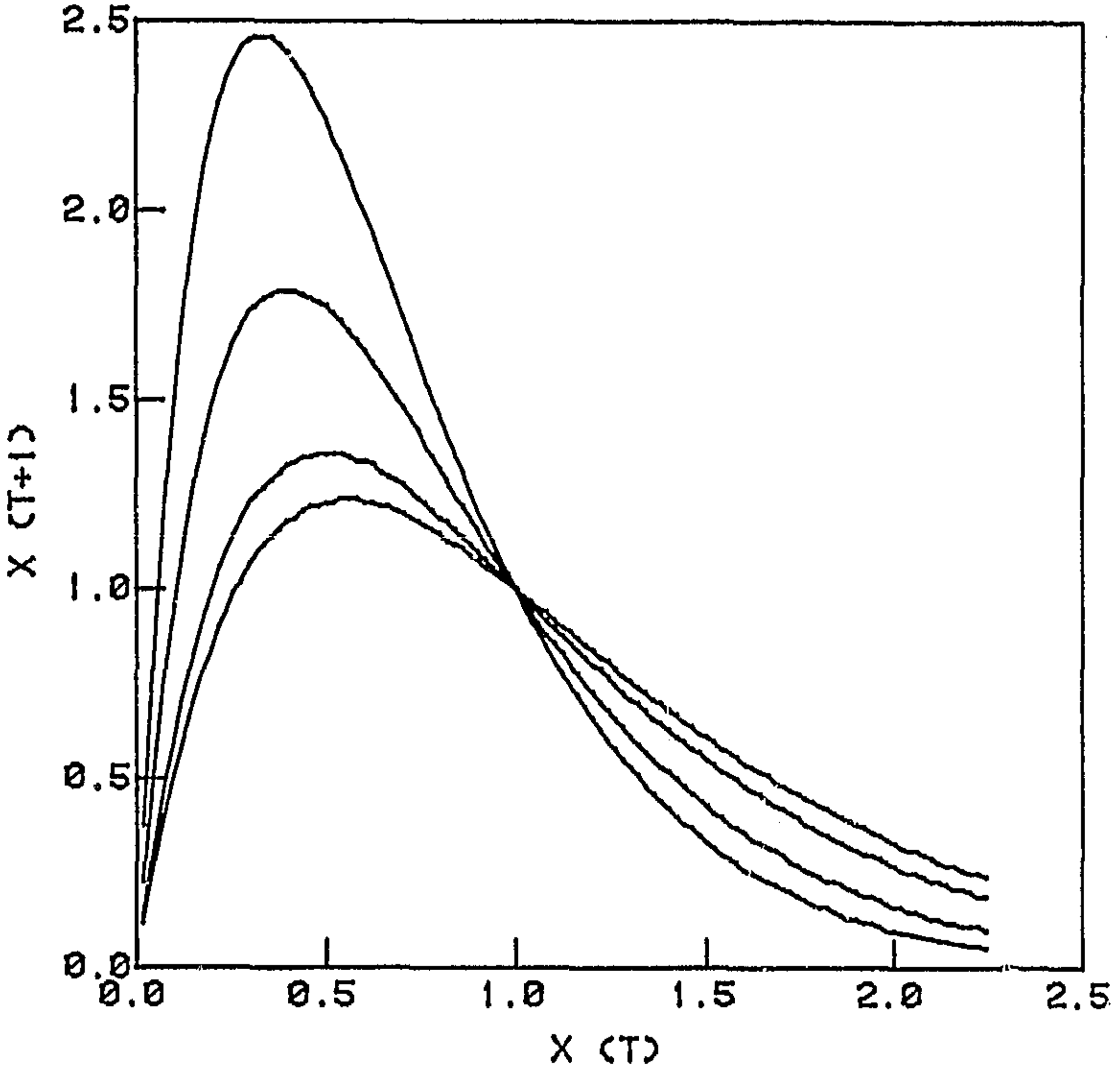


Figure 23: Relationship Between Successive Resource Levels as a Function of r

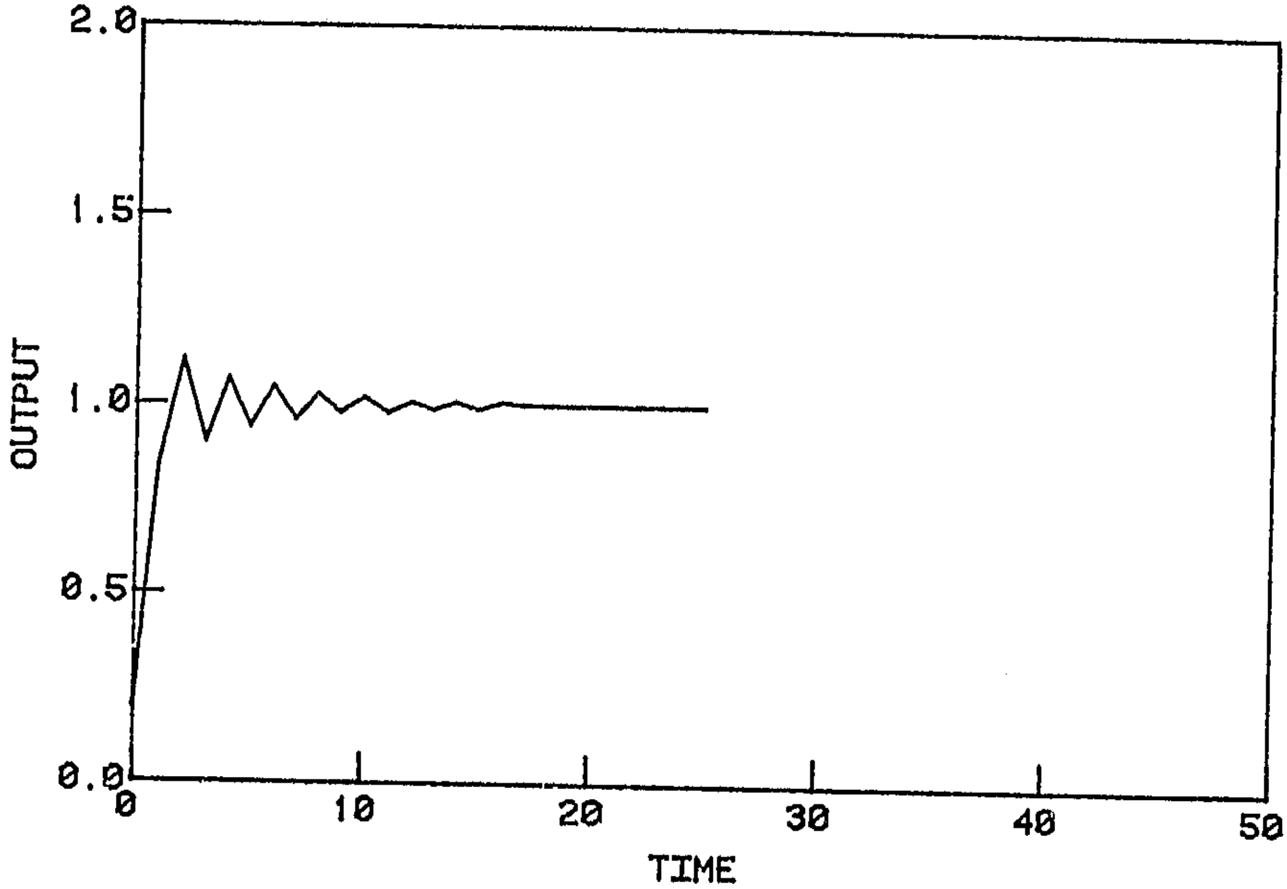


Figure 24: System Behavior with r=1.8

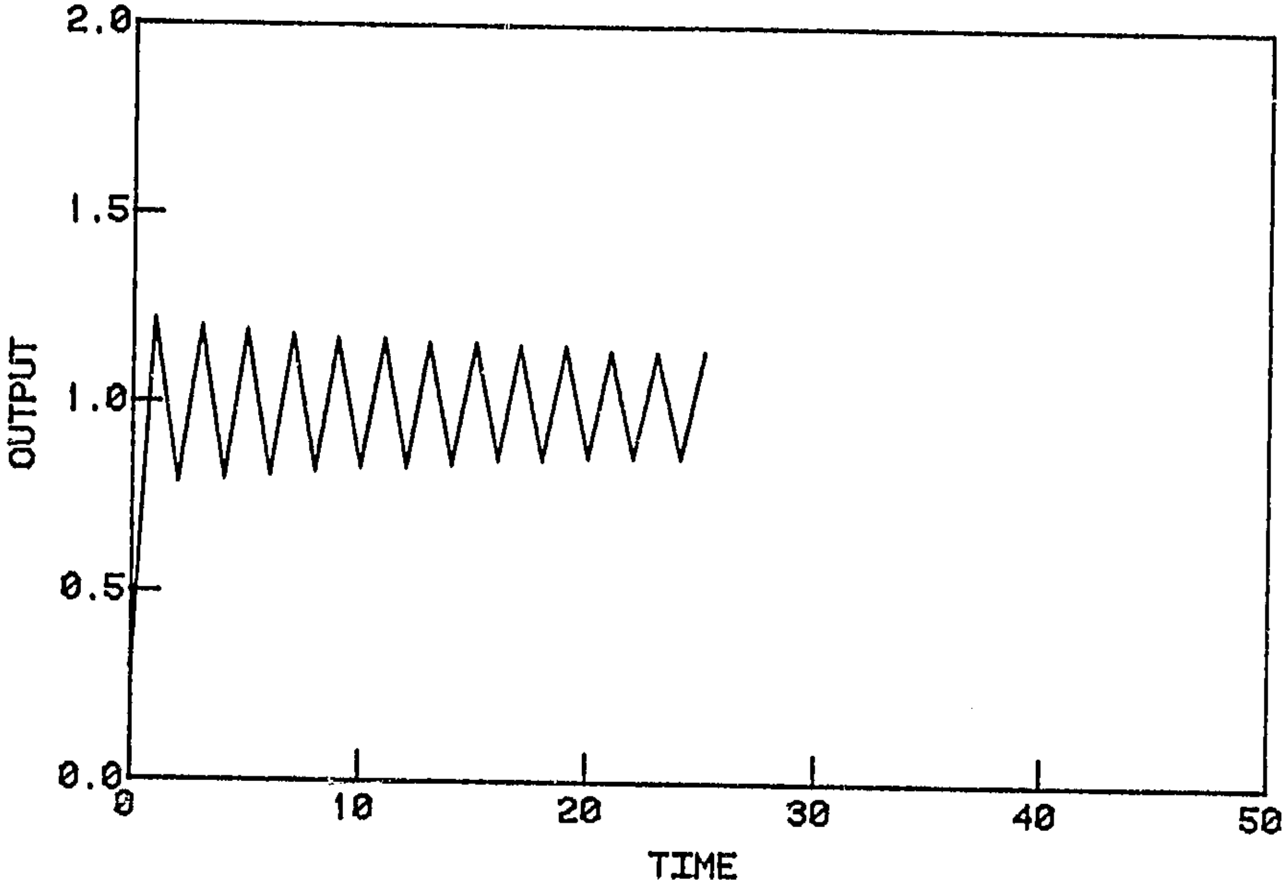


Figure 25: System Behavior with r=2

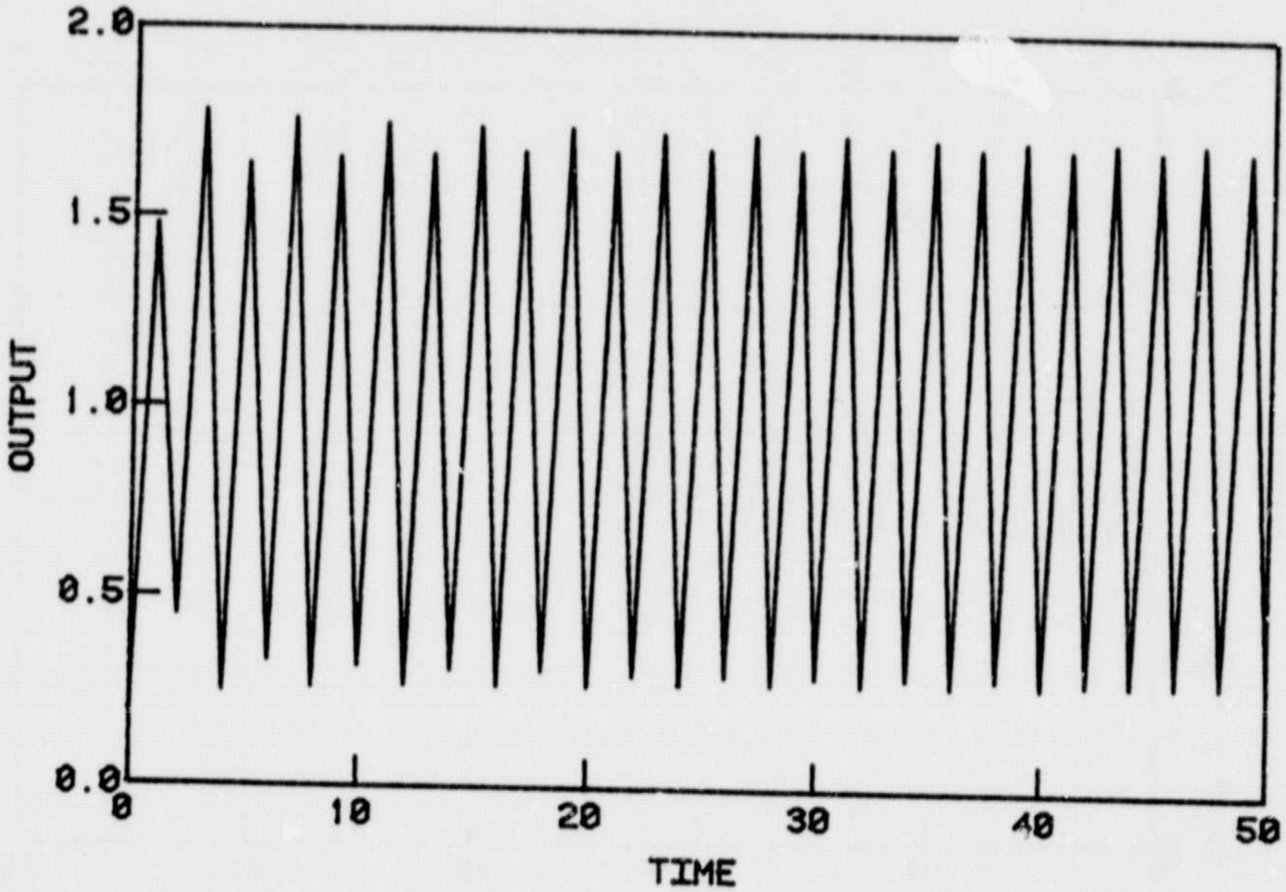


Figure 26: System Behavior with r=2.5

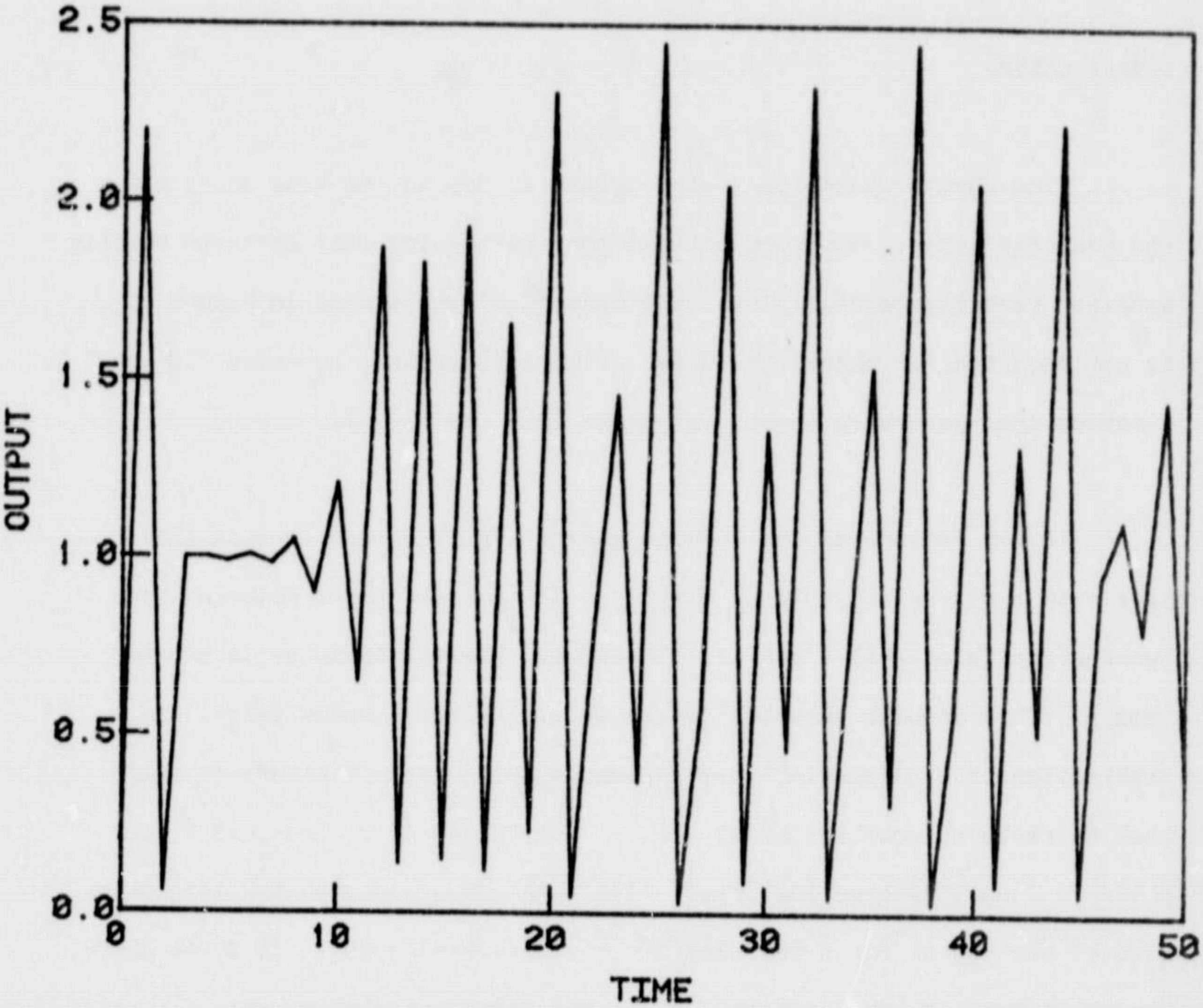


Figure 27: System Behavior with r=3

to the CELSS.

The chaotic behavior of the system is due to the time delay and the nonlinear gain. However, not all nonlinear gains will generate chaotic behavior (see Figure 24). Also, the functional shape used in Figure 23 is not required for chaotic results. Figure 28 shows a two-piece linear function that generates chaotic behavior (see Figure 29).

A key feature of the chaotic generating functions is that they have both a rising and falling portion. The turning point between these two regions is at $x(t) < x(t+1)$. Therefore, the rising slope is greater than 1. This insures that the origin is not an equilibrium point. An examination of the function that generated the curves in Figure 23 shows that there is an equilibrium at $x = 1$. For values of r less than 2 this point is locally attracting (Figure 24). As r increases past 2 this point becomes the center for a two step limit cycle (Figure 25). In other words, the equilibrium point has bifurcated. The bifurcation continues as r is increased until at $r > 2.71$ there is an infinity of resulting points. It should be noted that as r increases, the qualitative shape of the function (Figure 23) gets taller and steeper. It is this steepness that causes the chaotic behavior (as is demonstrated in Figures 28 and 29).

While it is interesting that such a simple dynamic system could generate such complex behavior, the connection between this abstract model and the CELSS needs to be established. The mass closure of the CELSS forces all resources to be either used or stored. However, it is necessary

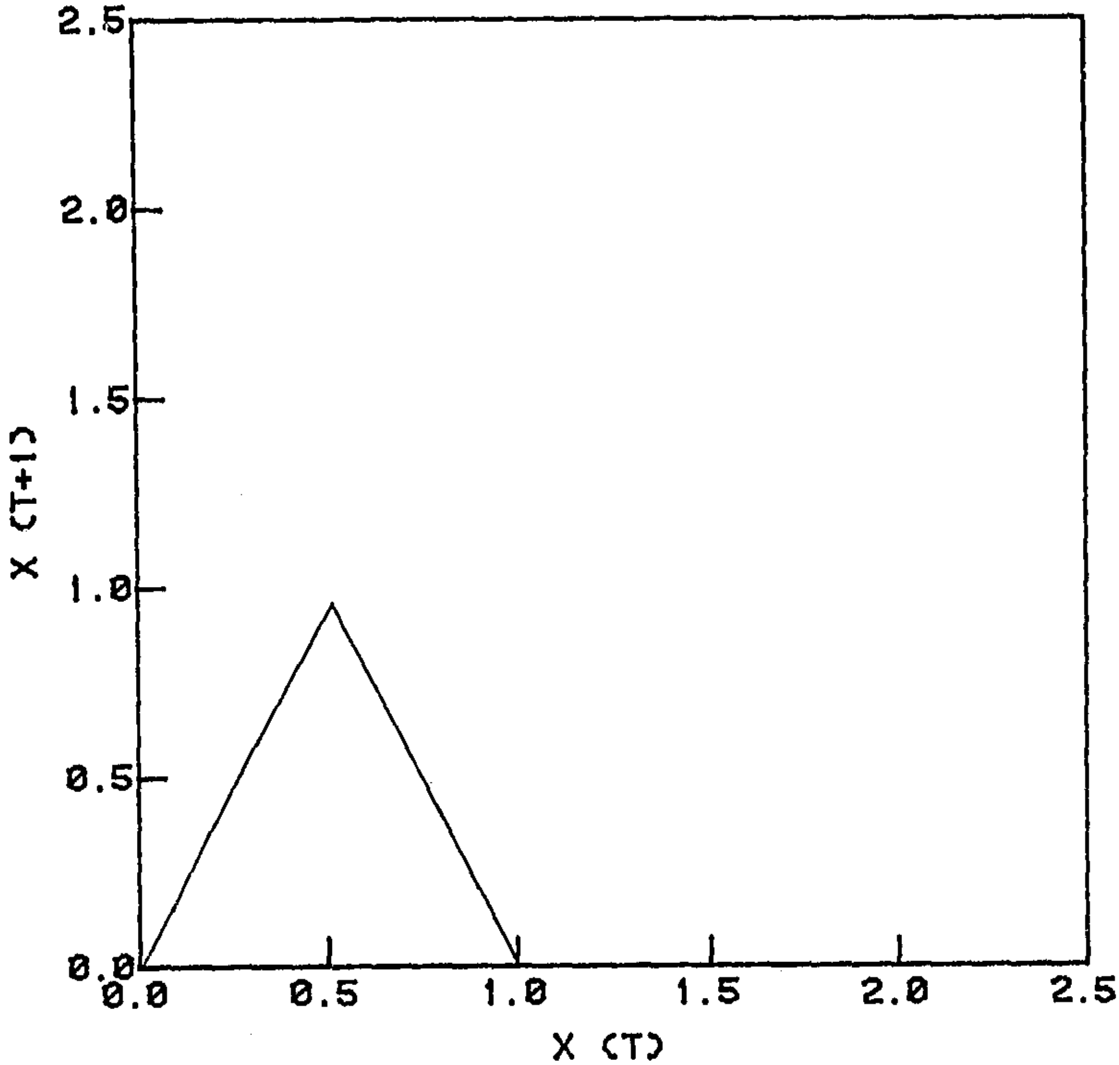


Figure 28: Bilinear Relationship Between Successive Resource Levels

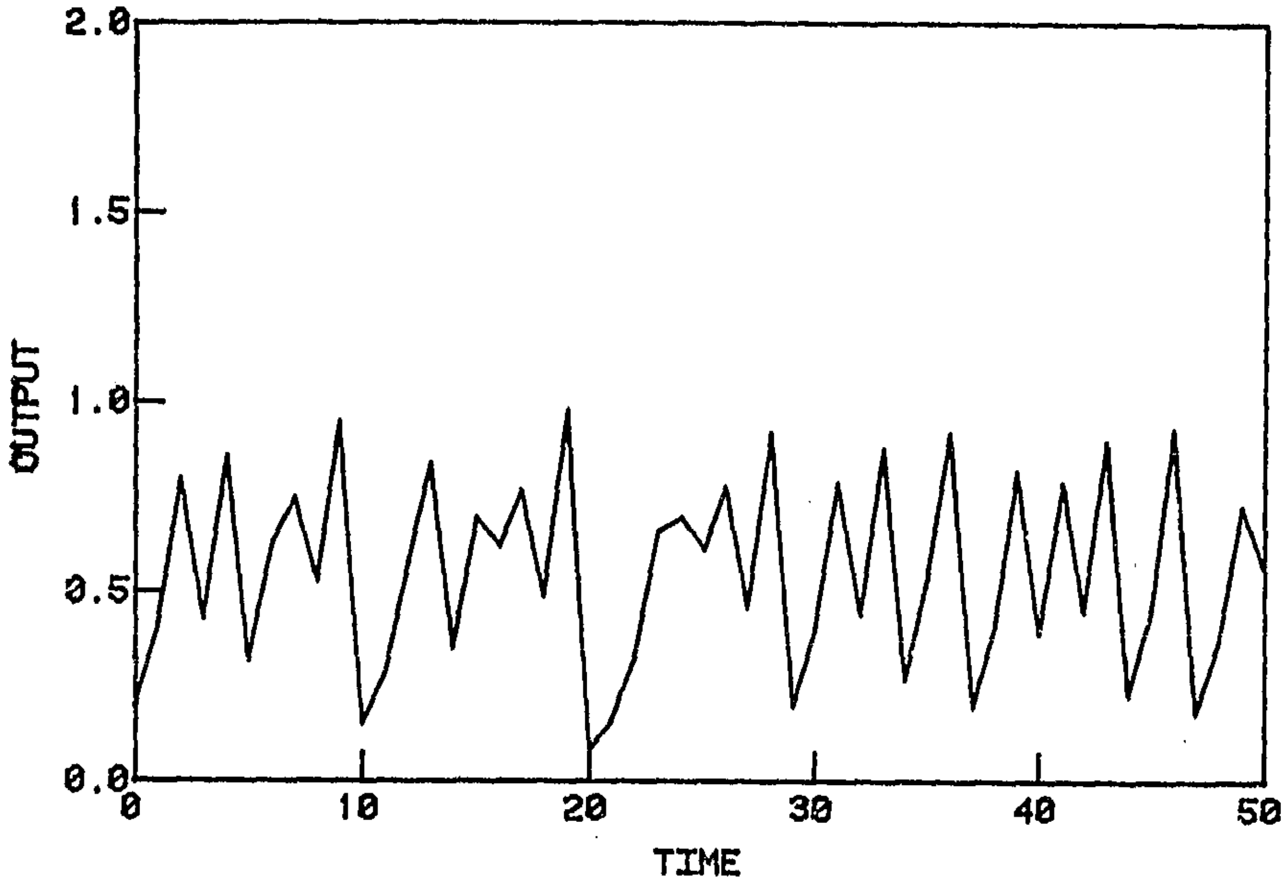


Figure 29: System Behavior with Bilinear Relationship

to minimize the storage areas for the system to be cost effective for space missions. Eventually a situation will arise where a storage tank is full but there are still resources waiting to be stored. Since all resources must be stored or used, some resources will have to be placed where they are detrimental to the system performance. This situation appears more likely when the wide range of processing times of the various CELSS components is taken into account. In fact, it becomes highly probable that the system will enter a chaotic regime if there is a component failure and the storage areas are sufficiently limited.

There are two potential solutions to avoiding getting stuck in the chaotic regime. First, all storage tanks could be increased in size so that it will be very unlikely that there would be a time when they are filled to capacity. Second, controllers could be developed to recognize situations leading into the chaotic regime and to move the system safely and quickly out of it. The second method is preferable to the first. Since there may be many other ways of entering into chaotic behavior besides the overflowing storage problem, a properly designed controller could still return the system to a more normal regime. Precise models of plant growth as a function of its environment have not been developed. This, coupled with our limited ability to monitor this growth, can easily create situations where an excessive amount of a resource is used on the plants and cyclic or chaotic behavior is initiated.

Work is needed to determine how a CELSS might move into a chaotic regime. Also, techniques need to be developed that can deal with the chaotic behavior and return the system to a better behaved regime. For

use in a CELSS, this control must be able to perform its task in an environment where the system parameters are uncertain and and there is already a substantial random component to the system behavior.

RESEARCH TASKS

The investigation of control of systems with delay and closure can be divided into two parts: dynamic systems and controls. The two field are interrelated. Control design is motivated by the undesirable aspects of the system model's behavior. Conversely, the motivation for modelling a system is to mimic its behavior so that controllers can be designed to improve the system performance. For clarity, we will discuss each separately. the following discussion will artificially separate them for clarity.

Work in dynamic systems revolves around the investigation of abstract models that contain delay terms. In particular, models which give nonintuitive behavior are candidates for examination. As shown above, the inclusion of nonlinear terms and mass closure in these simple models generates highly erratic behavior from very simple inputs. While there exists some discussion of the underlying mathematics of these systems in the literature, no connection has been made to a CELSS. An isolation of the specific aspects of the CELSS structure that generate these nonintuitive behaviors would be of use to future system design work.

Another point of interest is the examination of how a CELSS could migrate into these difficult to control regions. Unusual system behavior

may be limited to a start-up procedure, component failure, etc., or it may be more ingrained into the basic structure of the system itself.

Finally, as a preparation to controller design, the separability of the effects of the delay terms, nonlinear terms, and mass closure should be investigated. If they do separate easily then the control design problem is somewhat simplified.

In investigating controllers we attempt to reduce the undesirable effects noted in the abstract models. It has been shown that state variable feedback is effective in controlling a system which is characterized by a delay. In the case of a system with mass closure, nonlinear and delay terms, the control design is not as simple. The controller must be able to operate effectively in the chaotic regime and move the system efficiently out of it. It is advantageous for the controller to also be able to anticipate an impending transition into the chaotic regime and act accordingly. Throughout this process, the controller should be insensitive to system parameter uncertainty.

A benefit of these studies of systems with delay is the specification of measurements required for adequate control. Control which uses observations during the delay period is able to reduce many of the undesirable effects caused by the delay. These state variable feedback controllers, by requiring state information during the delay, increase the number of measurement devices needed in the system. When state measurements are difficult or impossible to obtain, an estimation of the state must be made. The requirements of both the estimator and the controller will then specify

the remaining system measurements needed for feedback control. However, the design of a reliable state observer in a nonlinear system with uncertain parameters is not a trivial task.

If CELSS component failure can lead the system into a chaotic regime, then measurement device failure or estimation error is also likely to cause nonintuitive system behavior. Therefore, the need for component and/or estimator redundancy must also be evaluated. The overall controlled system reliability will be due to a combination of the controller's insensitivity to uncertain parameters, the ability to estimate and/or measure the system's state, and the ability to cope with component failure.

The research tasks to be accomplished are:

a) Formulate abstract CELSS models that contain delay and nonlinear terms and mass closure.

b) Investigate the separability of the effects of these terms and the mass closure.

c) Identify aspects of CELSS structure which generate these behaviors.

d) Specify scenarios that lead a CELSS into these nonintuitive behaviors.

e) Examine the underlying mathematics of the system to aid in control design.

f) Design controllers that can operate in the chaotic regime and reliably move the system out of it.

g) Specify instrumentation and estimator requirements for the various control schemes.

h) Examine system reliability with various levels of component redundancy

References

Auslander, D.M. (1982). Spatial Effects on the Stability of a Food-Limited Moth Population. Journal of the Franklin Institute. Vol.314, No.6. pp.347-365.

Auslander, D.M., R.C. Spear, and G.E. Young. (1982). A Simulation-Based Approach to the Design of Control Systems with Uncertain Parameters. Trans. Amer. Soc. Mech. Engrs., J. of Dynamic Systems, Measurement and Control. 104:20-26.

Averner, M.M. (1981). An Approach to the Mathematical Modelling of a Controlled Ecological Life Support System. NASA CR-166331. NASA, Washington D.C.

Bellman, R. (1957). Dynamic Programming. Princeton University Press.

Bellman, R.E. and S.E. Dreyfus. (1962). Applied Dynamic Programming. Princeton University Press.

Fedra, K. (1980). Austrian Lake Ecosystems Study. International Institute for Applied Systems Analysis. Report CP-80-41.

Fedra, K. (1982). Environmental Modelling Under Uncertainty. International Institute for Applied Systems Analysis. Report WP-82-42.

Friedman, J.H., and W. Stuetzle. (1981). Projection Pursuit Regression. J. Am. Stat. Assn. 76:817-823.

Friedman, J.H., and W. Stuetzle. (1982a). Projection Pursuit Methods for Data Analysis. Modern Data Analysis. Academic Press.

Friedman, J.H., and W. Stuetzle. (1982b). Smoothing of Scatterplots. Project Orion. Dept of Statistics. Stanford University.

Gustan, E., T. Vinopal. (1982). Controlled Ecological Life Support System: Transportation Analysis. NASA CR-166420. NASA Ames Research Center, Moffett Field, California.

Hornberger, G.M. and R.C. Spear. (1980). Eutrophication in Peel Inlet: I. The Problem-Defining Behavior and a Mathematical Model for the Phosphorous Scenario. Water Research 14:29-42.

Hornberger, G.M. and R. C. Spear. (1981). An Approach to the Preliminary Analysis of Environmental Systems. J.Environ. Management. 12:7-18.

Howard, R.A. (1960). Dynamic Programming and Markov Processes. M.I.T. Press.

May, R.M., G. Oster. (1975). Bifurcations and Dynamic Complexity in

Simple Ecological Models. Amer. Natur. 110. pp. 573-599.

Spear, R.C. and G.M. Hornberger. (1980). Eutrophication in Peel Inlet: II. Identification of Critical Uncertainties Via Generalized Sensitivity Analysis. Water Research 14:43-49.

Spear, R.C. and G.M. Hornberger. (1981). A Technical Note on the SPS Energy Analysis of Herendeen et.al. Space Solar Power Review. 2:305-306.

Spear, R.C. and G.M. Hornberger. (1983). Control of DO Level in a River Under Uncertainty. submitted to Water Resources Research.

Stahr, J.D., D.M. Auslander, R.C. Spear and G.E. Young. (1981). An Approach to the Preliminary Evaluation of Closed Ecology Life Support System (CELSS) Scenarios and Control Strategies. InterSociety Conference on Environmental Systems.

Whitehead, P.G. and G.M. Hornberger. (1983). Modelling Algal Behaviour in River Systems. submitted to Water Research.

Young, G.E. (1982). A Design Methodology for Nonlinear Systems Containing Parameter Uncertainty. NASA Contractor Report 166358.

Controlled Ecological Life Support Systems (CELSS):
A Bibliography of CELSS Documents Published as NASA Reports

1. Johnson, Emmett J.: Genetic Engineering Possibilities for CELSS: A Bibliography and Summary of Techniques. (NASA Purchase Order No. A73308B.) NASA CR-166306, March 1982.

2. Hornberger, G.M.: and Rastetter, E.B.: Sensitivity Analysis as an Aid in Modelling and Control of (Poorly-Defined) Ecological Systems. (NASA Purchase Order No. A77474.) NASA CR-166308, March 1982.

3. Tibbitts, T.W.: and Alford, D.K.: Controlled Ecological Life Support System: Use of Higher Plants. NASA CP-2231, 1982.

4. Mason, R.M.: and Carden, J.L.: Controlled Ecological Life Support System: Research and Development Guidelines. NASA CP-2232, 1982.

5. Moore, B., and R.D. MacElroy: Controlled Ecological Life Support System: Biological Problems. NASA CP-2233, 1982.

6. Aroeste, H.: Application of Guided Inquiry System Technique (GIST) to Controlled Ecological Life Support Systems (CELSS). (NASA Purchase Order Nos. A82705B and A89697B.) NASA CR-166312, January 1982.

7. Mason, R.M.: CELSS Scenario Analysis: Breakeven Calculation. (NASA Purchase Order No. A70035B.) NASA CR-166319, April 1980.

8. Hoff, J.E., Howe, J.M., and Mitchell, C.A.: Nutritional and Cultural Aspects of Plant Species Selection for a Controlled Ecological Life Support System. (NASA Grant Nos. NSG-2401 and 2404.) NASA CR-166324, March 1982.

9. Averner, M.: An Approach to the Mathematical Modelling of a Controlled Ecological Life Support System. (NASA Contract No. NAS2-10133.) NASA CR-166331, August 1981.

10. Maguire, B.: Bibliography of Human Carried Microbes' Interaction with Plants. (NASA Purchase Order No. A77042.) NASA CR-16630, August 1980.

11. Howe, J.M., and Hoff, J.E.: Plant Diversity to Support Humans in a CELSS Ground-Based Demonstrator. (NASA Grant No. NSG-2401.) NASA CR-166357, June 1982.

12. Young, G.: A Design Methodology for Nonlinear Systems Containing Parameter Uncertainty: Application to Nonlinear Controller Design. (NASA Cooperative Agreement No. NCC 2-67) NASA CR-166358, May 1982.

13. Karel, M.: Evaluation of Engineering Foods for Controlled Ecological Life Support Systems (CELSS). (NASA Contract No. NAS 9-16008.) NASA CR-166359, June 1982.

14. Stahr, J.D., Auslander, D.M., Spear, R.C., and Young, G.E.: An Approach to the Preliminary Evaluation of Closed-Ecological Life Support System (CELSS) Scenarios and Control Strategies. (NASA Cooperative Agreement No. NCC 2-67) NASA CR-166368, July 1982.

15. Radmer, R., Ollinger, O., Venables, A., Fernandez, E.: Algal Culture Studies Related to a Closed Ecological Life Support System (CELSS). (NASA Contract No. NAS 2-10969) NASA CR-166375, July 1982.

16. Auslander, D.M., Spear, R.C., and Young, G.E.: Application of Control Theory to Dynamic Systems Simulation. (NASA Cooperative Agreement No. NCC 2-67) NASA CR-166383, August 1982.

17. Fong, F. and Funkhouser, E.A.: Air Pollutant Production by Algal Cell Cultures. (NASA Cooperative Agreement No. NCC 2-102) NASA CR-166384, August 1982.

18. Ballou, E. V. : Mineral Separation and Recycle in a Controlled Ecological Life Support System (CELSS). (NASA Cooperative Agreement No. NCC 2-53) NASA CR-166388, March 1982.

19. Moore, B., III, Wharton, R. A., Jr., and MacElroy, R. D.: Controlled Ecological Life Support System: First Principal Investigators Meeting. NASA CP-2247, 1982.

20. Carden, J. L. and Browner, R.: Preparation and Analysis of Standardized Waste Samples for Controlled Ecological Life Support Systems (CELSS). (NASA Cooperative Agreement No. NCA 2-OR260-102) NASA CR-166392, August 1982.

21. Huffaker, R. C., Rains, D. W., and Qualset, C. O.: Utilization of Urea, Ammonia, Nitrite, and Nitrate by Crop Plants in a Controlled Ecological Life Support System (CELSS) (NASA Cooperative Agreement No. NCC 2-99) NASA-CR 166417, October 1982.

22. Gustan, E. and Vinopal, T.: Controlled Ecological Life Support System: Transportation Analysis. (NASA Contract No. NAS2-11148) NASA CR-166420, November 1982.

23. Raper, C. David, Jr.: Plant Growth in Controlled Environments in Response to Characteristics of Nutrient Solutions. (NASA Cooperative Agreement No. NCC 2-101) NASA CR-166431, November 1982.

24. Wydeven, T.: Composition and Analysis of a Model Waste for a CELSS. NASA Techinical Memorandum 84368, September 1983.

25. Averner, M., Karel, M., and Radmer, R.: Problems Associated with the use of Algae in Bioregenerative Life Support Systems. (NASA Cooperative Agreement No. NCC 2-210) NASA CR-166615, November 1984.

26. Radmer, R., Behrens, P., Fernandez, E., Ollinger, O., Howell, C., Venables, A., Huggins, D., and Gladue, R.: Algal Culture Studies Related to a Closed Ecological Life Support System (CELSS). (NASA Contract No. NAS2-10969) NASA CR-177322, October 1984.

27. Wheeler, R., and Tibbitts, T.: Controlled Ecological Life Support System Higher Plant Flight Experiments. (NASA Cooperative Agreement No. NCC 2-136) NASA CR-177323, November 1984.